EXPLORING CONSUMER BEHAVIOR IN BANGKOK FOOD DELIVERY APPLICATION (FDA) MARKET: A BRAND PERFORMANCE ANALYSIS USING DIRICHLET MODEL

SIRAPHOB MAITREESIRIMONGKOL

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Siraphob Mait.
....
Mr. Siraphob Maitreesirimongkol
Candidate

Nathasit Gerdsri
....
Assoc. Prof. Nathasit Gerdsri,
Ph.D.
Advisor

Winai W
....
Assoc. Prof. Winai Wongsurawat,
Ph.D.
Chairperson

Vichita Ractham
....
Assoc. Prof. Vichita Ractham,
Ph.D.
Dean
College of Management
Mahidol University

....
Asst. Prof. Wanwiphang Manachotphong,
Ph.D.
Committee member

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Siraphob Maitreesirimongkol

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SIRAPHOB MAITREESIRIMONGKOL 6449192

M.M. (Marketing and Management)

THEMATIC PAPER ADVISORY COMMITTEE: ASSOC. PROF. NATHASIT GERDSRI, Ph.D., ASSOC. PROF. WINAI WONGSURAWAT, Ph.D., ASST. PROF. WANWIPHANG MANACHOTPHONG, Ph.D.

ABSTRACT

This research investigates the applicability and significance of the NBD-Dirichlet model by Goodhardt et al. (1984) as a benchmarking tool for brand performance measures (BPM) including average purchase frequencies and penetration rates across brands within the Food Delivery Application (FDA) category in Bangkok, Thailand. Moreover, the study seeks to uncover the inherent consumer behavior patterns within the market landscape including Double Jeopardy pattern and Duplication of Purchase law. The approach involves conducting an online questionnaire survey for the estimation of brand purchase over the previous month with 275 potential shoppers participated. The model's suitability varies based on the violation of underlying assumptions such as partitioned market or limited brand choices. The Double Jeopardy pattern and Duplication of Purchase law are identified in the market, indicating that larger brands perform better and attract switchers from other brands. Behavioral loyalty is found among exclusive buyers of the two largest brands. However, the model doesn't capture their marketing strategies or customer journeys.

KEY WORDS: NBD-Dirichlet/ Food Delivery Application (FDA)/ Double Jeopardy/ Duplication of Purchase/ Brand Performance Benchmarks

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CHAPTER 1: INTRODUCTION

Over several decades in the realm of consumer behavior, Andrew Ehrenberg and Gerald Goodhardt, the pioneers in marketing science study, and their colleagues have detected various empirical generalizations of consumer behavior. The following are some examples of inherited knowledge from their team. These generalizations include brand switching (Ehrenberg & Goodhardt, 1968), which reveals a poor link (low correlation) between one brand and another in the non-durable consumer product category. The Double Jeopardy Effect (Ehrenberg et al., 1990) is another major conclusion. It relates to the situation in marketing in which smaller companies have fewer customers and purchase less frequently than larger brands. The Duplication of Purchase law (Ehrenberg & Goodhardt, 1970) contributes to our understanding by stating that the proportion of one brand's customers who also buy another is proportional to the total number of buyers of each brand. These are some examples of empirical generalizations that highlight law-like aspects of consumers' brand choices based on Ehrenberg’s legacy.

In light of these generalizations, it becomes crucial for managers to carefully interpret the performance of brands (Bennett & Graham, 2010), particularly those with large market shares. Merely considering the purchase frequency of customers could be misleading, as it may solely indicate the brand's higher popularity in comparison to competitors. Therefore, it is imperative to discern whether a brand's performance aligns with the expectations set by the Double Jeopardy effect. To address this challenge, the utilization of the Dirichlet model, a stochastic model capturing and predicting the double jeopardy effects and duplication of purchases laws as proposed by Goodhardt et al. (1984), proves instrumental in benchmarking brand performance accurately. Since 1984, the model has been used in 50 different industries in both products and services (e.g., FMCG, Banking, TV programs, events, etc.) in varied locations (e.g., North Americas, Europe, Asia, South Asia, etc.), time periods, and market situations (e.g., stationary, near stationary, non-partitioned, partitioned sub-markets, etc.) (Ehrenberg et al., 2004; Drisener and Rungie, 2021).

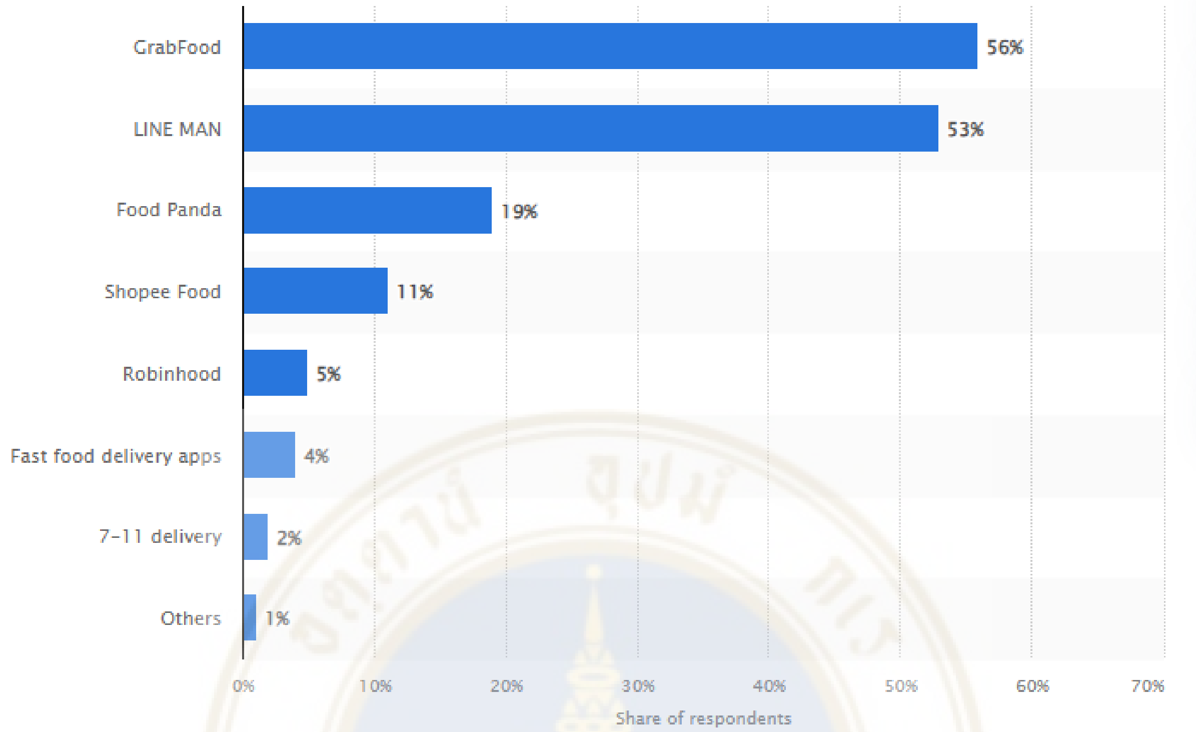
During the COVID-19 pandemic, consumers embraced the convenience of food delivery, and the market grew rapidly at first (Kasikorn Research, 2021). In 2022, each service provider was trying to explore the upcountry for new vendors and clients. In that year, a sense of familiarity has been developed, as seen by the slower growth rates of 2.9% in the predicted food order transaction index of 2022 compared to 2021.

However, once regulations were abolished and people returned to regular life, the demand for food delivery services decreased (Kasikorn Research, 2023a). Consumers reduced their use of food delivery, and the market diminished in the first quarter of 2023, with order rates falling by 8% (Kasikorn Research, 2023b). Rising raw material and energy costs intensified the difficulties, maintaining or increasing the average price each order. Online orders for beverages and pastry items fell while the basic and fast foods continued to perform well (Kasikorn Research, 2023a).

Despite these obstacles, food delivery platform providers have responded by expanding their markets, offering monthly packages (subscriptions), and broadening their offerings (Kasikorn Research, 2023c). They concentrated on strategy optimization, prioritizing marketing efforts for specific types of eateries, and assuring effective cost control. While the market value of the food delivery company was anticipated to fall (by 0.8-6.5%) in 2023, it remained greater than pre-pandemic levels on average.

Finally, these measures are indicating the increasing competition within Thailand's FDA environment. While category growth rates starting to decrease, the market became more competitive by the limited market size. Consequently, it is essential to create precise benchmarks that can help businesses gain a better understanding of their competitive position. The brands in competition, according to 19,339 respondents (Statista, 2023), are GrabFood (56%), Line Man (53%), Food Panda (19%), Shopee Food (11%), Robinhood (5%), and others (7%). As brands within this category have been well conveyed to customers for a period of time, indicating that the market is relatively stable, while the offers of each brand are basically the same in terms of ordering and delivering foods (with the exception of subscription models) according to the Dirichlet assumptions (*see NBD-Dirichlet Model)*. Therefore, this study is aimed to test and investigate the consumer behavior and actual brand performance underlying in the FDA market using the Dirichlet model as a benchmarks.

Figure 1: Most popular food delivery apps in Thailand as of April 2023 (Statista, 2023)



The goal of this study is to investigate the applicability of Andrew Ehrenberg's Dirichlet model in the setting of Thailand's Food Delivery Application (FDA) landscape, where this analysis has not previously been undertaken in the area (both geographically and industry). The major goal is to determine whether customers in the chosen industry comply with the Dirichlet model's empirical generalizations, which includes the duplication of purchase law and the double jeopardy effect in marketing. Furthermore, the study intends to evaluate the fit of the Dirichlet model to the observed data using systematic testing methods. Notably, the effectiveness of this research relies on certain assumptions about the market or industry being investigated. Specifically, it assumes that the market is unpartitioned, meaning that customers do not perceive significant differences between the products offered by different brands within the market. Additionally, it assumes a stationary market where brands do not require additional consumer learning, and advertising efforts have minimal impact. These conditions are central to the NBD-Dirichlet Model (Goodhardt et al., 1984; Sharp & Drisener, 2000; Drisener & Rungie, 2021) utilized in this study (*see NBD-Dirichlet Model)*.

Research Objectives:

1. To assess the applicability of the Dirichlet model in the context of the Food Delivery Application (FDA) market in Bangkok by evaluating the fit of the model with the observed data.

2. To examine whether customers in the selected Food Delivery Application (FDA) Market in Bangkok adhere to the empirical generalizations of the Dirichlet model, including the duplication of purchase law and the double jeopardy effect for each observed brand.

3. To provide insights into the potential implications of the findings for benchmarking the situation in the Food Delivery Application (FDA) Market.

Research Questions:

RQ1: Does the application of the Dirichlet model be good benchmarks across different brands' penetration rates and average purchase frequencies within the Food Delivery Application (FDA) Market?

RQ2: Do the customers in the Food Delivery Application (FDA) Market adhere to the double jeopardy effect (RQ2.1) and the duplication of purchase law (RQ2.2)?

RQ3: Does the Food Delivery Application (FDA) Market conform to the Dirichlet generalization patterns?

CHAPTER 2: LITERATURE REVIEW

1. NBD-Dirichlet Model

NBD-Dirichlet Model or Dirichlet Model, a stochastic model on negative binomial distribution (Goodhardt et al., 1984; Driesener & Rungie, 2021) designed as the descriptive model (Ehrenberg et al., 2000) indicating the empirical generalizations including double jeopardy, duplication of purchase law, and natural monopoly (Driesener & Rungie, 2021). The model requires the purchase occasions of each brand within a certain period in the stationary and unsegmented market while the longer period shows less loyalty from the customer which are its based assumptions (Goodhardt et al., 1984; Driesener & Rungie, 2021). The stationary market indicates that the category's customers are experienced with the product/service making it hard to be influenced with the short-term stimulation such as advertising (or there is no additional learning occurring) while the unpartitioned market indicates that the key attributes of product/service are appealing to be resembled to the category buyers then the buyers' brand choices are independence.

Figure 2: Result by Ehrenberg et al. (2004) showing the conformity between theoretical approximation of market shares compared to the observed data

Table 1
Annual penetrations and purchase rates (leading brands of instant coffee)

Instant coffee (USA 1992)	Market share (%)	Percent buying		Purchases (per buyer)	
		O	*T*	O	*T*
Folgers	24	11	*12*	3.2	*3.1*
Maxwell House	22	10	*11*	3.1	*3.1*
Tasters Choice	17	9	*9*	2.8	*3.0*
Nescafé	11	6	*6*	2.7	*2.9*
Sanka	9	5	*5*	3.0	*2.8*
High Point	1	1	*1*	2.6	*2.6*
Maxim	1	0.3[a]	*0.8*	4.5[a]	*2.6*
Brim	0.3	0.2	*0.2*	2.1	*2.6*
Other brands	16	8	*8*	3.0	*3.0*
The new Brand X	5	–	*3*	–	*2.7*

Data: Hallberg (1996)/MRCA; O = observed; *T = theoretical Dirichlet predictions.*
[a] Outlier.

Figure 2 from Ehrenberg et al. (2004) illustrates the close prediction between *T* (Theoretical Estimation) and *O* (Observation data). These theoretical predictions are derived by three parameters from category purchases including the market size (market shares), purchase frequencies of each consumer, and their brand choices. The model would provide the theoretical prediction based on the market shares of each observed brand and will be compared with the observed data to test the goodness of fit and analyze further with systematic methods by Driesener et al. (2017). As per previous studies, the theoretical result is likely to be close to the reality for brands under the underlying assumptions (Goodhardt et al., 1984; Sharp & Drisener, 2000; Bergström and Ones, 2013; Driesener & Rungie, 2021).

In the original paper by Goodhardt et al. (1984) the Dirichlet model is based on two core assumptions on the observed market. First, the observed market must be stationary. A stationary market is one in which aggregate measurements of purchasing behavior, such as sales, remain essentially constant throughout time, typically in the medium term. In a stationary market, there is little decay in the level of repeat purchasing, indicating that consumers have steady purchasing patterns. This is because the model assumes that consumers in the stationary market have an understanding of the brands and are difficult to persuade, or that no extra learning about the brands occurs (Ehrenberg et al., 2004). Finally, in a stationary market, regardless of individual purchasing behaviors, the total level of purchase remains constant from period to period (Driesener & Rungie, 2021; Bergström & Ones, 2013; Goodhardt et al., 1984). The second key assumption on the market is that the market should be an unsegmented or so called unpartitioned market (Goodhardt et al., 1984). The unsegmented market is one without discrete consumer subgroups or segments based on unique features or preferences of the offerings from each brand. In such a market, individuals' brand-choice probabilities are expected to follow the Dirichlet distribution. In a nutshell an unpartitioned market comprises no groupings of brands that compete with one another more closely than with the category (Bennett & Graham, 2010). Because there is no partition, the choice between different brands should be somewhat independent (Bergström & Ones, 2013; Goodhardt et al., 1984; Drisener & Rungie, 2021). Ehrenberg et al. (2004) come to the conclusion that, while many markets are stationary and nonpartitioned, this does not imply that all markets should be. They present a model that describes markets when they are mostly stable and not segmented. Even in less stable or clustered markets, however, the Dirichlet model still provides useful benchmarks for the managerial implications.

To address the core assumptions into the model, it incorporates five distribution assumptions (Bergström & Ones, 2013; Ehrenberg et al., 2004; Goodhardt et al., 1984). For product category purchases, the model adopts *Poisson distribution* (for individual purchases) and *Gamma distribution* (for the differences in average purchase rates of shoppers) while *Multinomial distribution* (for specific purchases) and *Multivariate Beta distribution* (for brand choice probabilities) are utilized to address brand choices. Lastly, the *Beta Distribution* (for the independence of purchase incidence and brand choice) to address the relationship between product category buying and brand choice. The application of the distributions are as follows:

1. Gamma Distribution - The Dirichlet model employs a gamma distribution on the assumption that consumers have varied average purchase rates in a product category. Unless the general average purchase rate is exceptionally high, this distribution represents individual variation, resulting in a small number of heavy purchasers and a higher proportion of light buyers. Based on these assumptions, a negative binomial distribution is used to describe the distribution of consumers who make varying quantities of category purchases. The gamma distribution was chosen because it could accurately represent the observed near-independence of purchasing different brands.
2. Poisson Distribution - The Dirichlet model utilizes the Poisson distribution to represent individual purchases. It is assumed that a consumer's purchases in a product category vary randomly across time, based on their projected average purchase rate. The likelihood of making a purchase is unrelated to when the previous transaction occurred. This assumption requires that the time periods be comparable in duration and not too short, as purchases made in one period should not influence those made in the next. The model yields the negative binomial distribution, which is used to represent the category distribution of purchases in the multi-brand Dirichlet model, by combining the Poisson distribution with the gamma distribution assumption for average buy rates.
3. Multinomial Distributions - The Dirichlet model uses the Poisson distribution to reflect individual brand purchases. It is assumed that consumers select a brand randomly on each purchase occasion based on their fixed brand choice probabilities. The chances of purchasing a specific brand are independent of previous purchase occurrences. This zero-order multinomial distribution of brand preference illustrates the behavior of consumers who, while they may have reasons for their selections, act as if they are making random judgments based on their personal probabilities. Even though a brand has a better utility in the deterministic component of the choice model, the presence of random error terms allows consumers to switch to a different brand. Overall, the brands are purchased in proportion to their fixed choice probabilities.

4. Multivariate Beta Distribution - Consumers are expected to have varied probability for selecting brands in the Dirichlet model, reflecting their variety in preferences. This variation in customer brand preference probabilities is represented by a multivariate Beta distribution known as the Dirichlet distribution. This distribution shows the variety in both the brand composition in consumers' repertoires and the likelihood of acquiring each brand. The Dirichlet multinomial distribution is generated by combining the Poisson distribution for individual purchases with the multivariate Beta distribution for brand choice probability. This distribution specifies how category purchases are distributed among different brands.
5. Beta Distribution (Independence of purchase incidence and brand choice) - The use of Beta distributions in the Dirichlet model implies that brand choice probabilities remain constant regardless of how frequently consumers purchase from the category. This means that the distribution of brand preferences is independent of purchase frequency. This assumption is validated both conceptually and experimentally (Ehrenberg et al., 2004), with market shares showing comparable trends among buyers in the light, medium, and heavy categories.

Goodhardt et al. (1984), Ehrenberg et al. (1990; 2004) and Sharp (2010) suggest that the observation metrics (e.g., purchase frequency or penetration) are usually close to the dirichlet estimation from the model outputs based on the exposures of each brand (e.g., market shares); if it's too low the brand might perform poorly compared to the usual state. This generates the managerial insights for managers by getting rid of the illusional aspect of benchmarking the performance of the brand. Past studies (Sharp, 2010; Ehrenberg et al., 2004; 1990) suggests that the loyalty score of consumers remains relatively consistent, regardless of the brand. However, the studies also reveal that larger brands, those with higher market shares, tend to have higher rates of customer penetration. As a result, the managerial conclusion is that brand penetration has more potential for growth by attracting more buyers while loyalty remains stable across all brands.

Bennett and Graham (2010) have described and summarized the common output as four Dirichlet patterns as followings:

1. Brand share is defined by the law of Double Jeopardy - This means that market shares and penetrations have a positive relationship. The bigger the market share, the greater the brand penetration, whereas the buy frequency has slightly altered based on market share. It implies that brand penetration may estimate brand size and consumer loyalty, and that the Dirichlet

model can determine if the observed brand is functioning as it should or not according to the double jeopardy effect.

2. Polygamous customer - Indicating that customers are polygamous in their brand selection and choose the brand only on a few occasions since they are experienced and choose the product based on a specific consideration set of two or three brands. As a result, Bennett and Graham come to the conclusion that "your buyers are the buyers of other brands who occasionally buy you." However, based on Ehrenberg et al. (2004), This pattern may not be found in the *subscription market*.

3. Hard-core loyalty exists, but mostly among light buyers - Only a few buyers are 100% repeat customers, although light buyers having fewer buying occasions have a higher likelihood of being considered loyal customers due to fewer switching opportunities. Furthermore, Goodhardt et al. (1984) stated that the longer observed period may better highlight the pattern.

4. Duplication of purchase is in line with brand penetration - The higher the brand penetration is, the more likely that the customer would switch to the brand in an unpartitioned market. This condition is except when two brands duplicated buyers have far-fetched higher buying rates in which showing an additional purchase.

To specify the existence of *subscription markets*, the work by Sharp et al. (2002) suggests that there are only two types of market patterns in competitive repeat purchase markets including *repertoire* markets (few sole buyers) and *subscription* markets (many sole buyers) in which the Dirichlet model fits well. The switching parameter (*S*), the heterogeneity measurement of brand choices estimated within the Dirichlet model, is the key separator for the market typology by the criteria. The fundamental criteria are that the subscription market's *S* value is below 0.2, whereas the repertoire market typically exceeds 0.6 and is often above 0.8. The literature further suggests that there is no empirical data of the value between 0.2 to 0.6. There are three types of the subscription markets suggested from the literature. Firstly, the Free Choice typology refers to markets where consumers have the liberty to choose from various providers without any restrictions, often found in industries with high sole buyer presence, such as credit card markets. The second type, Renewal type, comprises subscriptions designed for single use that await the renewal process, and their dynamics can be analyzed through metrics like switching rates or customer churn, common in sectors like home insurance. Lastly, the Tenure type encompasses markets allowing consumers to hold multiple subscriptions simultaneously, but the contracts remain in effect until actively terminated, typically observed in business-to-business settings like advertising agency contracts.

Drisener and Rungie (2021) discussed that the model still has certain limitations because it simplifies the purchase behavior regardless of purchase feedback from prior purchases, negative feedback from variety seeking behavior, and positive feedback from reinforcing effects. These limitations derive from the assumption that the consumer is experienced with the brands in the product category while there is no order in the models to trace back the purchase feedback.

In the preliminary stage, the model was calculated by hand by the pioneers (Drisener and Rungie, 2021), while the observation and theoretical prediction were analyzed qualitatively by observing and deciding how near the Dirichlet model can forecast the theoretical values to evaluate the findings. Drisener et al. (2017) addressed this issue with statistical analysis of the two outputs from the model between O and T (where *g* equals to number of brands), exploring into the literature review and data from various sources to test each benchmarking method to address the fit of the Dirichlet model, particularly for penetration and purchase frequency, as in *Table 1* with the criteria illustrated in *Table 2*.

Table 1: Goodness of fit equations (Drisener et al., 2017)

Methods	Equations
Comparison of Averages (AVE)	$AVE = \dfrac{\left\lvert \sum_{j=1}^{g} O_j - \sum_{j=1}^{g} T_j \right\rvert}{g}$
Comparison of averages between observed and theoretical estimation (AVE%)	$AVE(\%) = \dfrac{\left\lvert \sum_{j=1}^{g} O_j - \sum_{j=1}^{g} T_j \right\rvert}{\sum_{j=1}^{g} O_j} \times 100$
Average Absolute Errors (AAE) Often referred in other literature as MADs	$AAE = \dfrac{\sum_{j=1}^{g} \lvert O_j - T_j \rvert}{g}$
Mean Absolute Percentage Error (MAPE)	$MAPE = \dfrac{\sum_{j=1}^{g} \frac{\lvert O_j - T_j \rvert}{T_j}}{g}$
Relative Average Absolute Errors (RAAE)	$RAAE = \dfrac{AAE}{\frac{\sum_{j=1}^{g} O_j}{g}} = \dfrac{\sum_{j=1}^{g} \lvert O_j - T_j \rvert}{\sum_{j=1}^{g} O_j} \times 100$

Table 2: Goodness of fit criteria (Drisener et al., 2017)

Metrics	Methods	Fit Benchmark
Penetration	Correlation	≥0.9
	AVE (%)	≤ 5%
	RAAE	≤ 15%
	MAPE	≤ 20%
Purchase Frequency	Correlation	≥ 0.6
	AVE (%)	≤ 10%
	RAAE	≤ 20%
	MAPE	≤ 20%

Drisener et al. (2017) conclude that the observed behavior corresponds to the assumed purchase behavior when the model is fitted between observation and Theoretical estimation. This alignment may indicate that consumers use heuristics such as having different needs for buying the category (different average purchase frequencies across brands), being polygamous in buying behavior and buying from a set of repertoires, being a light buyer, and having constant brand choice probabilities in a short period (Driesener & Rungie, 2017). The inapplicability of the model can lead to different conclusions as the heuristics and assumptions may not work well. Therefore, in this case, the alternative marketing approach must be considered. In the end, the Dirichlet model can give useful benchmarks for brands' expected scores based on their size (market shares) in comparison to the observed data utilizing the test for goodness of fit (Ehrenberg et al., 2004; Drisener et al., 2017; Drisener & Rungie, 2021).

2. Double Jeopardy Effect

The Double Jeopardy Effects (Ehrenberg et al., 1990; Sharp, 2010) is an empirical law which identifies that brands with larger market shares would gain more purchase (also repeat purchase) and more liking attitudes towards them, and vice versa for the brands with smaller market shares. In practice, the bigger the brand is, the purchases per buyer will shift according to its market share which means that the brand with equal market share should have similar market penetration or attitudes or purchases depending on which metrics are measured (Sharp, 2010). Smaller brands have far fewer buyers and lower average purchase frequencies as the tendencies to be punished twice for being small (Ehrenberg, 2004; Sharp, 2010). This condition will occur except when the penetration rate of the specific brand is very high (Ehrenberg, 2004). The double jeopardy effect is based on the concept in which brands has different exposure and be beneficial from those exposures, first defined by McPhee (1963) as the "item that are similar but differ in popularity" while Ehrenberg et al. (2004) gives an example with when the audience learns that the brand has similar benefits (e.g. quality, service, value for money, accessibility, etc.) then the customer will "split their vote" because they are viewed equally by audience but the brand with higher popularity will get more score based on its recognition.

Not only did the large brand gain a larger customer pool and higher purchase occasions, Fader and Schmittlein (1993) suggests that the larger brand also benefits from the excess behavioral loyalty from the test in the Japan and U.S. consumer market. The excess behavioral loyalty occurs when large brands have higher repeat purchase than expected with the Dirichlet model. This phenomenon occurs only when the market is partitioned, not by violating other Dirichlet assumptions. Consequently, consumer segmentation becomes the primary determinant for the existence of this type of market share premium. For the underlying rationale, the authors suggest that brand availability is usually under distributed (less than 100% to the whole consumer group) while it associates with the brand shares, it makes the consumer only consider the limited choices that are available for them. Nevertheless, for the FDA category, the product takes the form of applications, which has not been observed thus far. However, we can infer that limited availability may arise when buyers exclusively download the application from highly popular providers.

3. Duplication of Purchase Law

The Duplication of Purchase law indicating that the proportion of buyers of certain brand who also buy the other brand in a time period is proportional to the total buyers of that particular brand (Ehrenberg & Goodhardt, 1970; Ehrenberg, 2004; Drisener & Rungie, 2021) while Ehrenberg and Goodhardt (1968) propose that there are low correlation between the purchase decisions of consumers when it comes to buying one brand of a non-durable consumer good and buying another brand within the same product category. In other words, the decision to purchase a particular brand does not strongly predict or influence the decision to purchase another brand in the same product category. Furthermore, Ehrenberg (2004) also stated that customers are usually polygamous in their brand choices by having several brands as their repertoire with 1-2 favorites while having only few 100% loyal (sole buyers). It was summarized by Sharp (2010) as “A brand’s customer base overlaps with rival brands in line with its market share. If 30% of a brand buyers also bought brand A in a period, then 30% of every rival brand’s customers also bought brand A."

Faulkner (2011) investigated the duplication of purchases in the donation business. To acquire data, they used open-ended questionnaires gathering the past donation for each brand per donor. The researchers focused on two crucial metrics which are penetration (*b*) and the Duplication coefficient (*D*). The Duplication coefficient (of the category) is calculated by dividing the average value of *b* by the average brand sharing in which adapted from Ehrenberg and Goodhardt (1970). To assess the validity of the Duplication of Purchase law, the researchers multiplied brand penetration by the Duplication coefficient, producing an expected share per brand. They then examined the relationship with the correlation test between average sharing per brand and expected sharing. As the result shows strong correlation, therefore, it supports the evidence that the Duplication of Purchase law is visible within the donation industry. Similarly, there are numerous studies that incorporate this approach, such as Bennett and Graham (2010) researching the duplication of purchase in the Thai car industry and Bennett et al. (2016) investigating the fashion market in Cyprus.

Table 3: Definitions of the Metrics (Ehrenberg et al., 2004; Rungie & Goodhardt, 2004; Goodhardt et al., 1984; Ehrenberg, 2004; Faulkner, 2011)

Metrics	Definitions
Shopper (respondent, panelist, etc.)	All potential buyers are recorded as the shopper (unit), regardless of their purchase decision whether they buy or not. A shopper may have a purchase rate of zero.
Buyers	Defined as the shopper who buys the product at least once, therefore their purchase rate must be greater than zero.
Purchase Rate (Buy Rate)	Buying quantity per buyer for each brand during a specific time period. Each shopper has separated the purchase rate for each brand within the category. The **Category Purchase Rate** is the combined total of the purchase rates for all brands.
Average Purchase Rate	Average purchase rate of the total shoppers which is divided into average purchase rate per category and per brand. The sum of the average purchase rate of each brand is the category average purchase rate.
Purchase Frequency	The average purchase rate of buyers for each brand and the average purchase rate of buyers for the whole category.
100% Loyals (Sole Buyers)	Proportion of buyers who buy only one brand which means that the buyer who purchases only one time (very light buyer) is categorized as sole buyer.
Duplication of Purchase (DoP)	Proportion of a brand buyer who also buys the other brand
Double Jeopardy	The fall in market shares and penetrations leads to a decrease in the number of buyers and purchasing occasions (average purchase frequency), resulting in "double jeopardy." This issue implies that being a smaller brand means being penalized twice, unless the brand has a high penetration rate.

Table 3: Definitions of the Metrics (cont.)

Metrics	**Definitions**
Market Share (%)	Total purchases of the brand divided by total purchases of the category
Penetration (%)	The number of buyers who have purchased the brand at least once divided the total number of potential customers (This thematic paper will use penetration (%) as Total Buyer divided by Shopper (Total Respondents)) referred to as B for the entire category and b for the specific brands based on Goodhardt et al. (1984). This research will use penetration (%) as Total Buyer divided by Shopper (Total Respondents).
Average Brand Sharing (%)	The "average brand sharing" is the average percentage of buyers who buy one brand and then buy another. For example, if 20% of Rolex customers also buy Casio and 16% of Omega customers also buy Casio, the average brand share for Casio is 18%. This reflects the average level of brand overlap or sharing among the client base.
Duplication Coefficient (*D*)	Average value of the penetration divided by the average brand sharing.
Expected Sharing Level (%)	The Expected Sharing Level would be calculated by multiply the Duplication Coefficient with the Average Brand Sharing

CHAPTER 3: RESEARCH METHODOLOGY

1. Sampling Plan

Several methods can be employed to capture the necessary data for this study. These include conducting a questionnaire survey, wherein respondents are asked to recall their purchase behavior within the category. Alternatively, panel data or data from loyalty cards provided by retailers could be utilized. Another option is employing a questionnaire utilizing the Juster scale and statistical approximation as proposed by Wright et al. (Wright et al., 2002; Bergström & Ones, 2013). Considering the time constraints and data availability, the most viable approach would involve an online questionnaire survey that directly captures the actual buying behavior of both consumers and non-users (potential customers) by making them recall their purchase occasions (Faulkner, 2011). This method ensures efficiency and convenience while providing valuable insights into the purchasing patterns of the target audience.

This study seeks to identify the consumer behavior lying under the brand purchase behavior in the selected category within Bangkok and nearby provinces (Nakhon Pathom, Pathum Thani, Nonthaburi, Samut Prakan, and Samut Sakhon). As for the scope of this study, the samples for this study are people who live in Bangkok or nearby provinces and have purchased any brands in the category on their own without any external subsidy (e.g. budget from workplace). Additionally, it is essential to note that individuals participating in the survey must be at least 18 years of age. This requirement ensures that respondents are legally recognized as adults and, therefore, do not require any parental authorization to participate. This research implies the quantitative method to analyze the data with the Dirichlet model. The quantitative survey was distributed and collected entirely online using a convenience sampling method to gather the required data based on the time constraints.

In this research we calculated the sample size according to the non-probability sample size formula as in the *Equation 1* (Vanichbuncha, 2003).

Equation 1: $$n = (Z^2 pq)/e^2$$

Since we do not know the current proportion of users in Bangkok and nearby areas, we will need to assume that the probability of adoption is equal (p = 0.5). Regarding the Z-score, it's a statistical measure used to calculate confidence intervals. For a 95% confidence interval, the Z-score equals 1.96. With this assumption and Z-score, we can proceed with the following equation:

From Equation 1: $n = (1.96^2 * 0.5 * 0.5)/0.05^2 = 384$

According to the result, the target sample size is 384. The collected data will be analyzed according to the *Quantitative Analysis Processes* to answer the research questions and generate the insightful implications.

2. Questionnaire Design

The questionnaire design comprises three sections. Firstly, it includes screening questions aimed at identifying individuals aged 18 years and above, who have resided in Bangkok or nearby areas for the past 6 months. These questions also inquire about participants' product usage within the specified time period (a month prior) while the defection from the respondents is also counted as the shopper buyrate. The second section focuses on brand choice and asks respondents to provide information regarding their purchase occasions for each brand. This section aims to gain insights into their preferences and behavior related to the Dirichlet Model and Duplication of Purchase Law. Lastly, the questionnaire includes a demographics section encompassing questions about income, age, and gender. This section aims to gather additional data on participants' characteristics to acknowledge the respondents' distributions.

3. Quantitative Analysis Process

According to the literature review, the questionnaires would collect solely the purchase frequency of each consumer and their brand preferences to calculate the required metrics (*Table 3*) on Microsoft Excel, which would then be input to Chen's (2022) NBDdirichlet model in RStudio. The outputs (penetration rates and average purchase frequencies of each brand) would be examined using the goodness of fit test (Drisener & Rungie, 2017) to answer the RQ1 and RQ2 using AVE, Correlation, RAAE, and MAPE as specified in the criteria (*Table 2*). For RQ3, the Double Jeopardy patterns would be revealed by the dirichlet model itself while the Duplication of Purchase laws will be calculated by hand according to the study by Faulkner (2011) using the correlation test between expected sharing level and average brand sharing, if the result has high correlation, then the Duplication of Purchase laws are visible.

Table 4: Class objects definitions used in Chen's R based tool (2022)

Metrics involved with the R based model by Chen (2022)	
cat.pen	Product category penetration, which is the observed proportion of category buyers over a specific time period.
cat.buyrate	Category buyers' average purchase rate in a given period. This is derived as the total number of category purchase occasions divided by the total number of category buyers during a time period.
brand.share	A vector of brand market share. We typically define it as the proportions of purchase occasions that belong to different brands during the time period.
brand.pen.obs	A vector of observed brand penetration, which is the proportion of buyers for each brand during the time period.
brand.name	A character vector of the brand names. If not given (default), use "B1", "B2", etc.
cat.pur.var	The observed variance of category purchase rates across individuals. It is used for the method of moment estimation of the parameter K in the Dirichlet model. If it is not given (default), then estimate K by "mean and zeros".
period.set	A member function of the "dirichlet" class object with one required parameter (t), which can be any positive real number. It resets the study time period to be t times of the assumed base time period in the sample.
t	Multiple of the base time period. For example, if the assumed base time period is quarterly, then t=4 would mean annually. Default to one.

CHAPTER 4: ANALYSIS

1. Descriptive Analysis of Respondents' Profiles and Distributions

Due to the limitations of time, a sample size of 275 was collected for the study. According to the Definitions table (*table 3)*, all the Bangkokians are assumed to be potential shoppers in which people who are over 18 and live in Bangkok and nearby areas are the potential shoppers. The final result in compliance with *table 5*, there are 207 people who are buyers (users) of the FDA category accounted for 83.81% while the other 40 people (16.19%) are non-buyers in the dirichlet model calculation.

Table 5: Respondents' Type

Respondents (Buyer and Non-Buyer)		
Types	**n**	**Proportion**
Total Respondents	275	-
Potential Shopper	247	100%
Buyers	207	83.81%
Non-Buyers	40	16.19%

For the buyers' demographics profiles, there are 138 female respondents (66.67%) while there are 69 men (33.33%). Then we separate the age range into 5 subgroups including respondents' ages between 18-24, 25-30, 31-40, 41-50, 51-60 and 61 or above. According to table *6*, the respondents skewed towards the left with a higher portion of younger consumers (73.43% of total consumers are younger than 30) and smaller proportion of older buyers. However, there are no buyers who aged 61 and above responded to the form at all. Initially, there are 5 groups of income range including under 15,000, 15,000-30,000, 50,000-70,000, and over 70,000 THB per month. The distribution of the income is also skewed towards the left side which is rooted from the higher portion of younger consumers who are undergraduates or working in the preliminary career that may receive lower income (under 30,000 THB per month). Even so, this skewness may be caused by the survey distribution of convenience sampling methods as the limitation.

Table 6: Respondents Demographics Distributions

Respondent Demographics (only buyers)								
Gender	**n**	**Proportion**	**Age Range**	**n**	**Proportion**	**Income Range**	**n**	**Proportion**
Male	69	33.33%	18-24	84	40.58%	<15,000	50	24.15%
Female	138	66.67%	25-30	68	32.85%	15,001-30,000	78	37.68%
			31-40	33	15.94%	30,001-50,000	37	17.87%
			41-50	7	3.38%	50,001-70,000	19	9.18%
			51-60	15	7.25%	>70001	23	11.11%

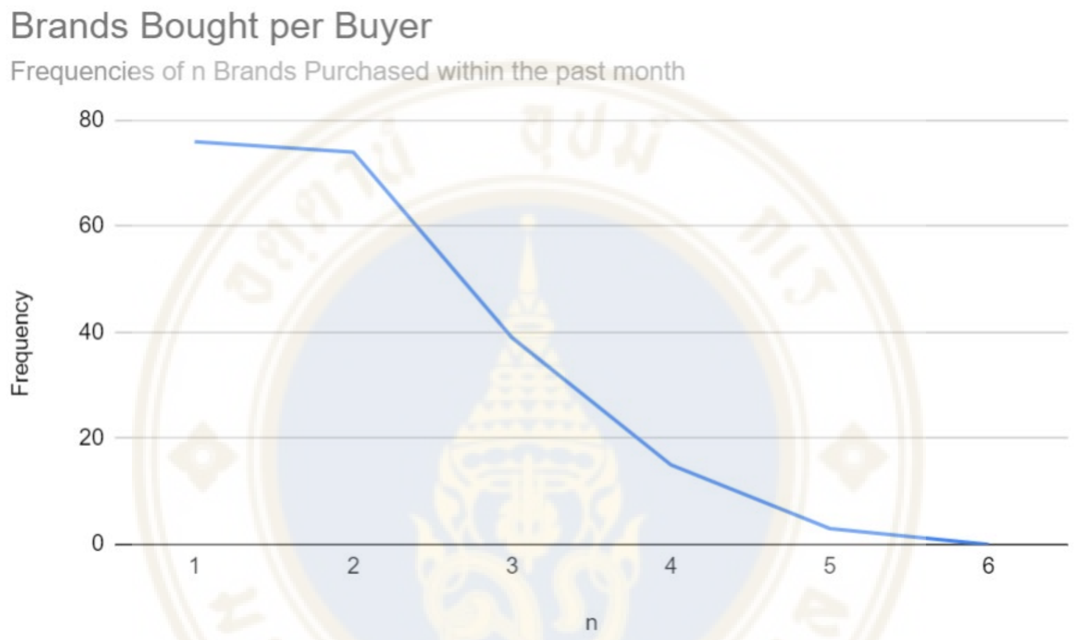
According to the brand popularity ranking by Statista (2023), there are 6 brands to be observed comprising GrabFood, Line Man, Robinhood, ShopeeFood, Foodpanda, and others within the category. There are two metrics involved including Brand Buyers and Brand Purchase Occasions illustrated in table 7. Brand Buyers represents the number of unique buyers for each brand. From the data, GrabFood has the highest number of brand buyers with 142, followed by LineMan with 133, Robinhood with 61, ShopeeFood with 46, FoodPanda with 24, and Others with 10. On the other hand, Purchase Occasions refers to the total number of times purchases were made for each brand. One unique customer can purchase one or many brands. GrabFood again leads in this metric with 794 purchase occasions, followed by LineMan with 751, Robinhood with 253, ShopeeFood with 154, FoodPanda with 64, and Others with 27.

In general, the relative popularity can be observed through these metrics. GrabFood and Line Man stand out as two most popular brands that dominate the market in terms of unique buyers and total purchases. These two brands have a distinct number of buyers as well as purchase occasions compared to the rest. To embellish the clearer picture, both GrabFood and Line Man have around 3 times more purchases compared to the Robinhood (3rd ranked player) and larger for the rest of observed brands.

Table 7: Number of Brand Buyers and Total Purchase Occasions for each brand

Metrics	GrabFood	LineMan	Robinhood	ShopeeFood	FoodPanda	Others
Brand Buyers (n)	142	133	61	46	24	10
Purchase Occasions	794	751	253	154	64	27

Figure 3: Non-Reverse J Shaped distribution of Number of Brands Bought per Buyer



This limited number of brands within the category may limit the potential of the Dirichlet model because it is a stochastic model assuming that all brand choices are randomly selected but when the choice is limited, as in Bangkok's FDA market, the choice may not be randomly selected by users. Furthermore, the market may not be unpartitioned as well which would affect the model estimations. To address the issue with more detail, *Figure 3* illustrates that there is a higher portion of buyers who bought only one to two brands within the category. The distribution of the number of brands purchased by distinct buyers deviates from the reverse J-shaped pattern proposed by Goodhardt et al. (1984). In contrast, it has a non-reverse J-shaped distribution with the case that the highest proportion of buyers bought only one brand. This implies that a higher proportion of users buy only a few brands, which contradicts the J-shaped distribution that a lower proportion of users would engage in such behavior.

2. Light, Medium, and Heavy Buyers

To understand the purchase behavior of buyers in the FDA category, one of the crucial parts is to segment buyers with their monthly purchase frequencies. This research utilizes Turkey's 5 numbers summary consisting of Min, Max, 1st Quartile, 3rd Quartile, and Median (*Table 8)* of total purchase per buyer to assist in identifying buyer types. The boxplot (*Figure 4)* illustrates the distribution of total purchase frequencies of each respondent and states that most of the users belong within the 1st Quartile and 3rd Quartile. As the result shows, the identification of medium users is people who use the FDA 4 to 14 times a month while people who use 1 to 3 times are identified as light users and 15 or more frequent are heavy users. In addition, the average purchase frequency per user is approximately 10 (9.87) times per single user per month.

Figure 4: Purchase Frequency per User (Boxplot)

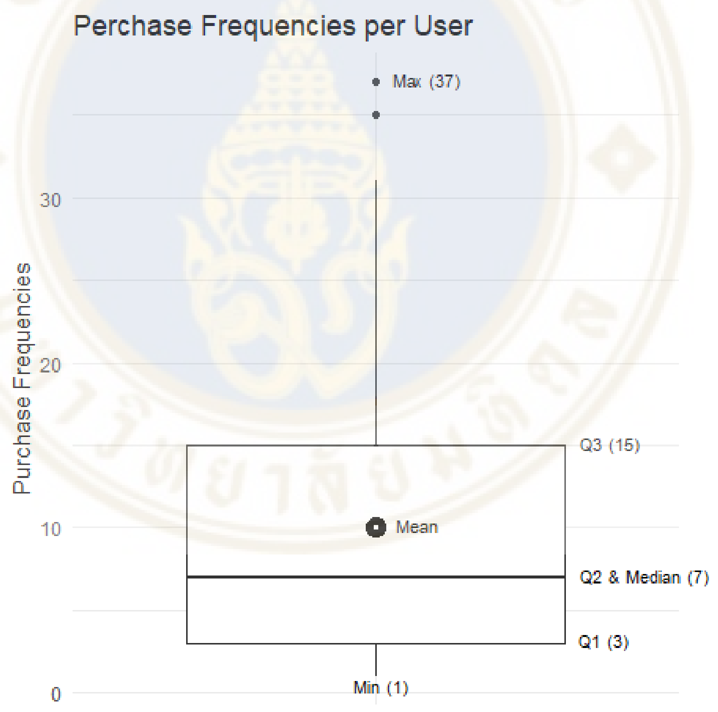


Table 8: Turkey's 5 Numbers Summary (with Second Quartile and Mean)

Purchase Occasions pur Buyer						
Mean	**Max**	**Q3**	**Q2**	**Q1**	**Min**	**Median**
10	37	15	7	3	1	7

3. Dirichlet Model Analysis

From the collected data, based on the R model by Chen (2022), there are 5 metrics required as the inputs for the Dirichlet model including Brand List (GrabFood, LineMan, Robinhood, ShopeeFood, FoodPanda, and Others), Observed Market Shares per brand, Observed Penetration Rates per brand, Category Penetration Rates, and Category Buyrate per Buyer illustrated in the *Table 9*. In that case, the result would consist of the model's approximated parameters, which encompass the Average Purchase Rate of the Category denoted as M, the Diversity of the purchase frequency for the category among buyers represented by K, and the Diversity of the consumers' propensity to purchase different brands labeled as S.

Table 9: Metrics for Dirichlet model's Inputs

Metrics	**Category Penetration Rates**		0.84	**Category Buyrate pur Buyer**		9.87
	GrabFood	**LineMan**	**Robinhood**	**ShopeeFood**	**FoodPanda**	**Others**
Purchase Frequencies	3.84	3.63	1.22	0.74	0.31	0.13
Brand Shares	0.389	0.368	0.124	0.075	0.031	0.013
Brand Penetration	0.575	0.538	0.247	0.186	0.097	0.040

The model by Chen (2022) was built to estimate three interrelated parameters between *M, K,* and *S.* The estimated values were resulting in *M=8.29, K=0.73,* and *S=0.09* according to *table 10*. According to the literature by Sharp et al. (2002), a market with an estimated S value below 0.2 can be considered a subscription market. Analyzing the nature of the application industry, it becomes evident that buyers in this market have the flexibility to choose from various competitors. Moreover, as illustrated in *figure 3*, numerous sole buyers who purchase only one brand are present more than expected to be the reversed-J shaped distribution pattern. As a result, the FDA category falls within the free choice subscription market definition.

The model examined a total of six observed brands, comprising five different brands and one category representing other brands out of the list. The Dirichlet model established the theoretical estimations (*T*) for each brand by examining market shares as an indicator of brand popularity. These estimations focused on brand penetration and average purchase frequency, providing insight into how the brands would perform in the market under Dirichlet conditions.

In *table 10*, the theoretical estimations of both metrics (Penetration and Average Purchase Frequency) have been estimated according to the double jeopardy effect where the higher shares the brand has the higher score in both metrics it will get estimated. For the two observed metrics (*O*) indicating the observation value based on market survey while the brands are sorted according to their size from large to small in the table. Initially, employing the conventional analytical approach by qualitatively comparing both *O* and *T*, it becomes apparent that the observed penetration rates significantly surpass the theoretical expectations derived from the model estimation. Conversely, the observed average purchase frequencies exhibit a shortfall in relation to the theoretical model, particularly among smaller brands with lower market shares. However, the observed (*O*) benchmark scores of both penetration rates and average purchase frequencies are aligned with its market shares even though their performance is not relying on the model benchmarkers. This leads to the presence of the double jeopardy effect because those observed metrics are following the brands' popularity. To confirm the statement with the correlation matrix between market shares and each observed metrics according to Bergström and Ones (2013), the results indicate that there are strong correlations (Correlation coefficient over 0.99 and P-value under 0.01) between penetration rates and market shares as well as the average purchase frequencies and market shares (*Table 11*). These results illustrate the double jeopardy effect within the FDA category in Bangkok. In addition, the correlation also confirmed that the larger brands have higher penetration rates accordingly. Furthermore, within the market landscape, GrabFood and Line Man have emerged as dominant players, outperforming other competitors significantly by capturing 75.62% of total market. In fact, their performance outperforms that of the lowest-performing brand ("others") by ten folds.

Table 10: Dirichlet Model Results

Model Estimations		$g = 6$	$M = 8.29$	$K = 0.73$	$S = 0.09$
Dirichlet Model Result	**Brand Shares (%)**	**Brand Penetration**		**Average Purchase Frequency**	
		T	**O**	**T**	**O**
GrabFood	38.86%	0.36	0.57	8.76	3.84
LineMan	36.76%	0.35	0.54	8.73	3.63
Robinhood	12.38%	0.12	0.25	8.31	1.22
ShopeeFood	7.54%	0.08	0.19	8.19	0.74
FoodPanda	3.13%	0.03	0.10	7.95	0.31
Others	1.32%	0.01	0.04	7.53	0.13

This study also incorporates statistical tests for goodness of fit approach from Drisener et al. (2017) rather than using solely the conventional qualitative interpretation method in order to serve two purposes. First, to confirm the existence of the double jeopardy effect and second, to confirm the applicability of the Dirichlet model as the benchmarks in the food delivery application (FDA) industry. As mentioned in the *literature review section*, the test for the goodness of fit consists of Correlation, Comparison of averages between observed and theoretical estimation (AVE%), Mean Absolute Percentage Error (MAPE), and Relative Average Absolute Errors (RAAE). In the case of FDA category, according to table *12*, it passes only the correlation criteria in both metrics (penetration rates and average purchase frequencies) indicating the unfit of the overall model for being a benchmarker.

Table 11: Correlations between Market Shares and Other Metrics

Penetration and Market Shares	Correlations 0.994657324845263	P-Value 0.0000427400
Average Purchase Frequency and Market Shares	Correlations 0.999998801144082	P-Value 0.000000000002155882

Firstly, we should discuss the first test, the correlation between the variable *O* and *T*. This test aims to seek for their relationship isolatedly whether it is concurrent or not (Drisener et al., 2017). In the context of the FDA industry in Bangkok, the findings show strong correlations that pass the established criterion (Table 12) in both metrics. In addition, the correlations are the only criteria that passed the test for model's goodness of fit. Furthermore, based on the researcher's observation, it also assesses the presence of the double jeopardy effect by considering that the theoretical estimations of the Dirichlet model inherently incorporate the phenomenon at its basis. Therefore, the strong correlation between both observed metrics and its own corresponding theoretical estimations could also relate to the existence of the double jeopardy effect in the FDA market.

Table 12: Test for the goodness of fit

Dirichlet Benchmark	**Brand Penetration**		**Average Purchase Frequency**	
	Fit Score	**Fit Benchmarks**	**Fit Score**	**Fit Benchmarks**
Correl	0.995883	>=0.9	0.91837	>=0.6
Correl P-Value	0.000025	<0.01	0.00972	<0.01
AVE (%)	43.786982	<=5%	401.21581	<=10%
RAAE (%)	148.630952	<=15%	80.87355	<=20%
MAPE (%)	43.786982	<=20%	401.21581	<=20%

Nevertheless, as mentioned, the model estimations cannot surpass the rest of the criterias including AVE%, RAAE, and MAPE. According to Driesener et al. (2017), these combined metrics (AVE%, RAAE, and MAPE) reflect the applicability of the model with the observed data by comparing the averages, relative absolute errors, and mean absolute percentage error. In Table 12, the fitness scores for both penetration rates and average purchase frequencies (excluding correlations) are unexpectedly exceeding the fitness criterias. Specifically, the observed AVE% of average purchase frequencies is approximately 40 times higher than the expected benchmark criteria of under 10%, which indicates a significant deviation from the expected range. The category average purchase frequencies of the respondents may be the root cause inflating the model estimations for the average purchase frequencies to be significantly higher than it should. On the other hand, the predicted penetration rates are significantly lower than the actual performance for every observed brand in the category.

Based on *table 18* that indicates the distribution of buying patterns, which the skewness in brand usage arises, in which brands with higher market shares (particularly the two largest brands, GrabFood and Line Man) attract a larger proportion of heavy users and account for a significantly higher proportion of sole buyers (buyers who buy only one brand within the observed period). This result emerges from the analysis in which the Dirichlet assumption about the unpartitioned market may not be true in the Bangkok FDA landscape. The literature by Fader and Schmittlein (1993) has captured this phenomenon as one of the benefits for large brands that would naturally have the market share premium when the market is partitioned based on the limited availability of choice. To clarify further, while the FDA's distribution should ideally be 100% accessible to all potential shoppers, there could be instances where buyers exclusively download only the most popular applications or stick to their preferred choices. This behavior may result in limited mental and physical availability for smaller brands, causing potential challenges for them to reach their audience effectively. As a result, shown in *table 18*, there is evidence of behavioral loyalty that exists within the FDA market.

From the rationale, the Dirichlet assumption about the partitioned market may not be true in the Bangkok FDA landscape. Furthermore, the unfitness of the results would also emerge from the fact that the assumptions of the model are abused by the limited choice in the market. In conclusion, these resulted in the lack of the model as the benchmarker for brand performance within the food delivery application industry in Bangkok.

4. Duplication of Purchase Analysis

Table 13 illustrates the total buyers for each observed brand that would be the basis of the calculation for the cross-buying proportion in *table 15*. To recap, as previously specified, buyers refer to individual shoppers who have purchased the product at least once, meaning their purchase rate must be above zero. Consequently, these buyers may choose to purchase a single brand or multiple brands, and it is important to further investigate their cross-buying behavior and relationships in more depth. However, the larger brands (based on its market shares) capture a far larger number of buyers than the smaller brands.

Table 13: Total Buyers of each brand

Brands	GrabFood	LineMan	Robinhood	ShopeeFood	FoodPanda	Others
Total Brand Buyers (n)	142	133	61	46	24	10

In order to calculate the duplication of purchase proportion (n of cross buyers between two brands/n of total brand buyers) the relationships between each two brands should be investigated. As *table 14*, illustrates the number of buyers who cross buys between two brands for the calculation process. Prior to that, it was found that more than half of each brand's buyers purchased from the two largest brands. For example, 37 out of 61 Robinhood buyers purchased GrabFood and 38 purchased Line Man.

Table 14: Number of User who cross-buys between two brands

Switcher (N)	GrabFood	LineMan	Robinhood	ShopeeFood	FoodPanda	Others
GrabFood	-	84	37	34	17	7
LineMan	84	-	38	34	15	6
Robinhood	37	38	-	15	6	5
ShopeeFood	34	34	15	-	9	1
FoodPanda	17	15	6	9	-	3
Others	7	6	5	1	3	-

Table 15, the duplication of purchase table, consolidates the data from two preceding tables (*table 13* and *table 14*). It provides comprehensive analysis of the proportion of switchers for each two brands in the observation. The relationship can be interpreted in two aspects between the vertical columns and horizontal rows in order to understand the consumer behavior. Vertically, it indicates the proportion of buyers for a particular brand who also buys from other brands. For example, the first column of *table 15* illustrates the proportion of GrabFood buyers who also buy from other brands. On the other hand, horizontally, it displays the proportion of buyers of a particular brand who purchase from other brands. For instance, the first row of *table 15* illustrates the proportion of buyers from all observed brands who also purchase GrabFood. To be specific, the horizontal line indicates the extent of cross-brand purchases from customers to each particular brand. In addition, this

paper defines the vertical and horizontal lines in the duplication of purchase table alternately compared to other studies (Faulkner, 2011; Bergström and Ones, 2013).

Table 15: Duplication of Purchase Table (Rounded)

Proportion of brand byers who also buy from others (%)		**Duplication Coefficient** ($\frac{28}{35}$)		0.80	**Average Sharing Across All Brands**		35
					Average Penetration		28
Brands	**Brand Pen.**	**GrabFood**	**LineMan**	**Robinhood**	**ShopeeFood**	**FoodPanda**	**Others**
GrabFood	**57**	-	63	61	74	71	70
LineMan	**54**	59	-	62	74	63	60
Robinhood	**25**	26	29	-	33	25	50
ShopeeFood	**19**	24	26	25	-	38	10
FoodPanda	**10**	12	11	10	20	-	30
Others	**4**	5	5	8	2	13	-

For this case, as illustrated on *table 16*, the averages of each brand that gained switcher from others (horizontal rows in *table 15*) would represent the average proportion of users from other brands who switched to a particular brand. In order to systematically investigate the evidence of the duplication of purchase law, the correlation between expected duplication and the average switcher proportion must be analyzed. The duplication coefficient can be derived by finding the average brand penetration rate, which stands at 28, and subsequently dividing this value by the mean of the average switcher proportion per brand, measured at 35. Consequently, the computed duplication coefficient is 0.8 as in *table 15*.

For the preliminary analysis of the table, as mentioned with *table 14*, there are high proportions of switchers from other brands buying larger brands while the switcher proportion is decreasing for smaller brands based on the results from *table 15* and the average switcher proportion from *table 16*. This can be viewed as the underlying consumer behavior from duplication of purchase law that is defined as a situation where the proportion of cross-brand buying behavior among a brand's buyers, who also purchase from other brands, is proportional to the total number of buyers for that brand. However, the qualitative observation alone is insufficient to make a concrete statement. As a result, two tests are adopted to reveal the existence of duplication of purchase law in this scenario.

To begin with the first method used by Faulkner (2011), it involves the calculation for expected duplication for each brand. This calculation is based on the multiplication of its penetration rates and the duplication coefficient. Subsequently, the method is required to examine the correlation between expected duplication and the average of switcher's proportion for each brand. The second approach is the adaptation from Bennett and Graham's (2010) argument on Dirichlet pattern. The objective is to ensure a consistent relationship between each brand's average switcher proportion and its penetration rates. The strong correlation between these two metrics would confirm the existence of the duplication of purchase law in the sample group. Furthermore, it also emphasizes that the proportion of duplicate buyers of a certain brand is relative to the number of its buyers.

Table 16: Expected Duplication Table (Rounded)

Expected Duplication Table				
Brands	**Market Shares**	**Penetration Rates**	**Average Switcher Proportion**	**Expected Duplication**
GrabFood	39	57	68	54
LineMan	37	54	64	51
Robinhood	12	25	33	26
ShopeeFood	8	19	25	20
FoodPanda	3	10	17	13
Others	1	4	7	5

Table 16 displays the metrics under investigation including market shares, penetration rates, average switcher proportions (from horizontal lines of *table 15*), and expected duplications. The average proportion of switchers per brand demonstrates that when the brand sizes are larger (measured by market shares), the brand would acquire a larger proportion of purchases from other brands' customers accordingly. The tests according to Faulkner (2011) and Bennett and Graham (2010) are summarized in *table 17*, revealing notably strong correlations (correlation coefficient > 0.99 with P-value < 0.001) for both methods. This finding strongly supports the presence of the duplication of purchase law in the Bangkok FDA market according to the literature review even when the market condition

differs from assumptions due to the lack of brand choices in the category and the mental and physical availability issues.

Table 17: Correlations between Average Switcher per Brand and Other Metrics

Average Switcher per Brand and Expected Duplication	Correlations 0.999941848773093	P-Value 0.0000000051
Average Switcher and Penetration	Correlations 0.998937568466357	P-Value 0.0000016925

5. Loyalty Behavior Analysis

Lastly, for the purpose of delving down to the details on customer loyalty behavior, *table 18* illustrates the distribution of repeat purchase behavior of each brand's buyer. However, this analysis is not the orthodox approach used by any other practitioners, but it will use the gathered data to comprehend the purchase behavior in depth. To start with the distribution of the number of brands purchased by customer, it is differed from the original paper in which predicted that usual distribution would be in the shape of reversed-J by having lower sole buyers (100% loyals) who purchase only one brand compared to buyers of two brands or more. The result from *figure 3* stated that the largest group of buyers in the FDA category are purchasing only one brand within the time period which may affect the model's assumptions. Moreover, the estimation of *S* value analyzed with the nature of the business can lead to the conclusion that the FDA market is a free choice subscription market. Nevertheless, the literature by Sharp et al. (2002) suggests that there should be a larger proportion of loyalty buyers for each brand (over 54% when *S* parameter is dropped down to 0.2), but in the FDA market, the proportion is only 25% at maximum.

Subsequently, as defined in the *2. Light, Medium, and Heavy Buyers section*, the segments based on purchase frequencies can be investigated further. One of the observed consumer behavior patterns according to the Dirichlet model is that there is a relatively small proportion of sole buyers (100% loyals) for each brand compared to the larger number of buyers who frequently switch between brands (Goodhardt et al., 1984; Bennett and Graham, 2011). Additionally, the literature review supports the finding that loyal buyers are mostly light buyers in terms of their purchasing frequency due to the assumption that the market is unpartitioned and the user choices are not limited.

Since the assumptions including the unpartitioned market and the as if random choice are violated, there are certain proportions of 100% loyals for each brand, especially two largest brands (GrabFood and Line Man) that capture over 20% of loyal consumers while the rest have only 10% or lower. The data presented in *table 18* provides evidence that, while the two largest brands have a significant number of loyal and heavy buyers, the majority of loyal customers are actually light buyers who make purchases no more than three times a month. Moreover, the analysis indicates that, apart from Robinhood, the other brands follow the patterns described in the literature review, with only a small number of loyal buyers who are predominantly light buyers.

Based on observed data, there are a large number (approximately half of the total sole buyers per brand) of heavy and medium buyers who are sole buyers for those two brands while the smaller brands clearly have a lower number of sole buyers. As mentioned in the *Dirichlet Model Analysis* section, this incidence can be called the excess behavioral loyalty as a result of the double jeopardy effect that would occur when there is market segmentation (partitioned) based on the availability of the product both mentally and physically. Therefore, the larger brands in FDA market are not only beneficial from the higher number of buyers and purchase incidences but also the higher rates of excess behavioral loyalty.

Consequently, these findings occur along with the arguments about the observation period and the brand choices within the market that may affect the overall models. As the proportion of both switcher and loyal buyers are distributed towards the two leading brands, it is well illustrated that the market has been partitioned which makes the baseline assumption of the Dirichlet model failed to be the benchmarker due to the significance disparity between *T* and *O*. On the other hand, this research asks the shopper for their purchase occasions of the FDA category within only one month. This may affect the overall models in both the Dirichlet model and the Duplication of purchase proportion because the period could be too short to reflect more of the switcher(s) as the larger period would show the lower number of 100% loyal buyers for each brand (Goodhardt et al., 1984; Bennett and Graham, 2011).

Table 18: Distribution of the consumer segment based on purchase frequencies and switching behavior

Brands	GrabFood	LineMan	Robinhood	ShopeeFood	FoodPanda	Others
100% Loyals	36	28	7	2	2	1
Proportion of 100% Loyal	25.35%	21.05%	11.48%	4.35%	8.33%	10.00%
Heavy Loyal	5	4	0	0	0	0
Heavy Switcher	7	4	4	0	0	0
Heavy Total	12	8	4	0	0	0
Medium Loyal	11	10	4	0	0	0
Medium Switcher	46	52	11	17	5	2
Medium Total	57	62	15	17	5	2
Light Loyal	20	14	3	2	2	1
Light Switcher	53	49	39	27	17	7
Light Total	73	63	42	29	19	8

6. *Share of Category Requirements (SCRs)*

In the switching scenery of purchase patterns, we can utilize Shared of Category Requirements (SCR) to help explain the loyalty behavior used by Ehrenberg et al. (2004). It represents the proportion of average purchase frequencies of all brands compared with (divided by) the total average buy rate. Generally, as shown in *table 19*, the average SCR in the category is 17% indicating that there is an 83% propensity of buyers of one brand to allocate their purchase to other brands. This result also confirms the multi brand buying behavior according to the literature. In detail, higher share brands including GrabFood and Line Man covered the market with a combination of its average SCR at 75% showing that the larger brand benefits from the double jeopardy compared to the rest of the smaller brand.

Table 19: Share of the Category Requirements (SCRs)

Share of Category Requirements per Brand					**AVG** = 17%
GrabFood	**Line Man**	**Robinhood**	**ShopeeFood**	**FoodPanda**	**Others**
40%	35%	12%	7%	4%	2%

7. Dirichlet Model Analysis without Violation

Sharp and Driesener (2000) has suggested that the baseline assumptions are very critical for the Dirichlet model because the unexpected deviation(s) can affect the theoretical estimations. Before then, the literature suggests that there are four main consumer behaviors that also cause deviation from the underlying assumptions including Segmentation, Functional Difference, Distribution, and Variety Seeking effects. Therefore, after the analysis on the current market situation with segmentation effects and the limited brand choices, the two outliers that strongly perform which are GrabFood and Line Man should be cut away to test the benchmark ability of the model for the competition of smaller brands.

With 148 shoppers remaining after the removal process. The new model accounts for 108 buyers and 40 non-buyers, resulting in the overall penetration rates of 0.7 or 70% with the category buy rate at 4.6 times per buyer. By estimating *M* as 3.22, *K* as 0.7, and *S* as 0.2, the market is thereby defined as the similar *subscription market*, determined by the value of *S*.

In *table 20*, with the traditional approach by Goodhardt et al. (1984), the result has shown close estimation between *O* and *T* in brand penetration while the average purchase frequency is still too far. However, to delve down to the statistical test for the goodness of fit, the same criterion by Drisener et al. (2017) is also adopted. The results in *Table 21* have shown that the approximation of penetration rates has passed almost all criterias except the AVE% while the average purchase frequency passed only correlation criteria. The pass in correlation criteria illustrates the Double Jeopardy pattern suggesting that the phenomenon continues to exist within narrower segments of the competitive environment.

In the context of the fitness of models using other examination methods, the model predictions on average purchase frequencies remain inadequate as a benchmarker. Hence, there are noteworthy insights hidden in the prediction of the penetration rates once they pass MAPE% and RAAE% criterion, even in cases where AVE% is scored higher than the criteria. This highlights the potential of the Dirichlet model to be a valuable benchmark on penetration in this submarket compared to inapplicability of the model in the total market.

Table 20: Dirichlet Model Results (without GrabFood and Line Man)

Category Penetration = 0.7				**Category Buyrate** = 4.6	
Brand	**Shares**	**Brand Penetration**		**Average Purchase Frequency**	
		O	**T**	**O**	**T**
Robinhood	0.51	0.41	0.42	2.34	3.94
ShopeeFood	0.31	0.24	0.27	1.43	3.69
FoodPanda	0.13	0.15	0.12	0.59	3.48
Others	0.05	0.06	0.05	0.25	3.39

Table 21: Test for the goodness of fit

Benchmarks	**Penetration Rates**	**Fit Benchmarks**	**Average Purchase Frequencies**	**Fit Benchmarks**
Correl	0.99	>=0.9	0.99	>=0.6
AVE%	9.85%	<=5%	68.20%	<=10%
MAPE%	14.62%	<=15%	493%	<=20%
RAAE%	9.30%	<=20%	68.2%	<=20%

CHAPTER 5: CONCLUSIONS AND IMPLICATIONS

1. Conclusions

This chapter seeks to summarize the feasibility and usefulness of the Dirichlet model as a benchmarker in the context of FDA market as well as reveal the underlying consumer behavior patterns in the market. Our research questions revolve around two main areas: first, exploring the potential of the Dirichlet model as a reliable tool for market analysis and benchmarking in the FDA industry in Bangkok, and second, unraveling the underlying marketing patterns (e.g., Double Jeopardy and Duplication of Purchase patterns) that govern consumer choices within these markets.

RQ1: Does the application of the Dirichlet model be good benchmarks across different brands' penetration rates and average purchase frequencies within the Food Delivery Application (FDA) Market?

Based on the analysis using the Dirichlet model to benchmark the performance of brands within the FDA market, the assessment of goodness of fit suggests that the model is not suitable to be the benchmark tools in the observed population. The AAE%, RAAE%, and MAPE% tests between the Theoretical estimations (*T*) and Observed data (*O*) both in penetration rates and purchase occasions indicate that it does not align with the benchmark criterion proposed by Drisener et al. (2017). These outcomes are affected by the deviation on certain model assumptions. To begin with, the assumption on the equal probabilistic purchase choice is not happening because there is a limited set of brands within the competitive market. Secondly, the analysis of the excess loyalty behavior revealed that there are significantly higher loyal customers with heavy buyers who are sole buyers to the large brands. The existing literature (Fader and Schmittlein, 1993) has explained the root of the situation as when the market is segmented due to the constraints in brand availability affecting the brand repertoires of the customer. The further analysis about the excess behavioral loyalty will be mentioned further in RQ 2.1 section.

Other than the test within the total market, certain applicability of the model has manifested in the submarket after removing the two leading brands with excess behavioral loyalty. The model exhibits the capability to benchmark the penetration rates of the submarket, fulfilling the fitness criteria except the AVE%. Although, the model still cannot benchmark the average purchase frequencies for the submarket. In summary, it is advisable to apply the Dirichlet model to the entire market to observe market patterns. In situations where there are deviations from the underlying assumptions, conducting tests for the remaining brands can serve as a valuable method to benchmark their performance.

RQ2: Do the customers in the Food Delivery Application (FDA) Market adhere to the double jeopardy effect (RQ2.1) and the duplication of purchase law (RQ2.2)?

For RQ 2.1, the Double Jeopardy effect is confirmed by the tests for correlations between a variety of metrics according to literature by Bergström and Ones (2013), Drisener et al. (2017), and Bennett and Graham (2010). The literature supports the validation of Double Jeopardy by the test between *T* and *O* results because the theoretical estimations of the Dirichlet model have aggregated the double jeopardy effects from the market shares (brand popularity metric) already. Moreover, the test between the *O* metrics and market shares directly is also encouraged by the literature. The tests have been done for both penetration rates and average purchase frequencies as the brand performance metrics. The results have shown strong correlations with the coefficient over 0.99 and the P-value under 0.01. This empirical result illustrates that the higher market shares brands have is moving along with the brand's performance metrics. In the end we can conclude that there is the presence of the double jeopardy effect within the Bangkok FDA category. However, it is important to note that the correlation serves as a test for the visibility of Double Jeopardy effect but not referring to the cause of it (e.g., variety seeking behavior or reinforcing effects).

Along with the literature (Ehrenberg et al., 1990; Sharp, 2010; Ehrenberg, 2004), the presence of Double Jeopardy is reflected in the FDA market as the brands that possess larger market shares would gain larger advantages in terms of purchase frequencies and number of buyers while the smaller brands get punished according to their size. These are the two general advantages in the Double Jeopardy market pattern. Therefore, the brand with higher shares may achieve high brand performance benchmarks naturally when using the comparison on number of sales or number of users while it is vice versa for small brands. This reason may lead to the point where the descriptive analysis on ordinary brand performance measures (e.g., number of sales and its growth rates) cannot benchmark performance when this market pattern occurs. Consequently, it is crucial for marketers to utilize consumer models (e.g., NBD-Dirichlet model) to help understand their brand's performance with a more realistic point of view. For example, in this case, the smaller brands can adopt the model to see their past performance with double jeopardy pattern in account.

For the further analysis on the double jeopardy advantage for larger brands, when there is any market partition occurs due to the under distribution of product or service, the literature by Fader and Schmittlein (1993) suggests that there would be the excess behavioral loyalty pattern. It is the phenomenon that larger brands have a higher number of loyal customers than expected because they have better distribution that increases the chance to become the brand repertoire of any consumer. Even though, this research has not been testing for the root cause of the excess behavioral loyalty in observed market, but there are some hypotheses for the cause of both mental and physical availability that can be infer based on the literature such as the actual physical availability due to some exclusive restaurants in certain application leading to different functional value, the number of price promotion that affect the penetration rates, or the mental availability from when buyers are considering only the brand that they have exclusively downloaded on their mobile devices that limiting the accessibility of the alternatives. Hence, all these examples are the possible cause of the deviation of the excess loyalty in higher shares brands which needed to be observed in further study.

Within RQ 2.2, the examination evolved around the outlines by Fuakner (2011), and Bergström and Ones (2013). It seeks for the correlations between the average switcher proportion per brand and two measures, including expected duplications and penetration rates. The outcomes revealing strong correlations in both measures indicate the existence of a duplication of purchase pattern within the Bangkok FDA category. By the results, it indicates that brands in the same category share customer base together. The proportion of switchers has exhibited the market pattern that the higher the penetration the brand has the higher chance that other brand buyers would switch to them. On the other hand, we can call that the proportion of switchers is proportional to the number of brand buyers according to Ehrenberg and Goodhardt (1970), Ehrenberg (2004), and Drisener and Rungie (2021). Furthermore, based on the literature, sole buyers generally are only a few groups in any category, however, with the excess behavioral loyalty, there are distinct portions of sole buyers for two largest brands while the smaller brands have quite the same portion of sole buyers. With the literature by Sharp (2010) and Ehrenberg et al. (2004; 1990), we can conclude that the brand would grow along with the higher penetration rates and capturing more of the switchers and light users.

RQ3: Does the Food Delivery Application (FDA) Market conform to the Dirichlet generalization patterns?

In RQ 3, the researcher adopts the conclusion of the patterns by Bennett and Graham (2010) that involves around 4 areas of the generalization.

RQ3.1: Do brands shares defined by the law of double jeopardy in the FDA market? This pattern involves the influence of brand popularity (market shares) that affects the brand performance measures. The inquiry has been investigated in both RQ1 and RQ2. As a result, it is viable to deduce the validity of the generalized statement presented in RQ 3.1 by having the presence of the Double Jeopardy pattern in the FDA market.

RQ3.2: Do customers in the FDA market have polygamous purchase behavior? RQ2.1 has answered this question already by analyzing the switch purchase behavior in the market with the test that showed the presence of the duplication of purchase law. The majority of brands exhibit a similar pattern of having a limited number of exclusive buyers, except for the two leading brands which gain advantages through higher levels of excess behavioral loyalty. Ultimately, the typical consumers of these brands tend to have multiple brand choices, as indicated by both the analysis of purchase duplication and loyalty. Consequently, the comprehensive tests of purchase duplication and loyalty demonstrates that the predominant consumer behavior involves being polygamous in their brand preferences, commonly referred to as brand switching, despite the slight influence of excess behavioral loyalty on the two major brands.

RQ3.3: Are the majority of loyal customers who exclusively purchase a single brand characterized as light buyers, with a few segments comprising heavy buyers? In the Loyalty Behavior Analysis, the primary findings indicate that a significant portion of buyers engage in brand switching behavior, while specific segments exhibit one brand purchasing behavior, often referred to as loyalty. Despite the market functioning as a subscription model, it follows a free choice type definition, which leads to lower tendencies for customers to exhibit loyalty compared to traditional subscription markets that buyers usually exclusively use one brand. The examination reveals distinct loyalty patterns, with two brands with the excess behavioral loyalty boasting distinct loyal consumer proportions of 25 and 21 percent, whereas others have smaller proportions of sole buyers, ranging from 4 to 10 percent of their total customer base. Notably, the three least prominent brands lack heavy sole buyers, and the leading brands also have limited instances of such buyers. The majority of loyal customers, in this context, primarily fall within the category of light buyers, with only a few segments representing heavy buyers.

RQ3.4: Does the duplication of purchase follows the trend of brand penetration Existing literature indicates that an increase in brand penetration results in a higher percentage of customers switching to that brand, thereby expanding its user base. This phenomenon has been observed in the unsegmented markets. Interestingly, despite the FDA market's deviation from this assumption due to its partitioned nature, the same trend is identified within this market as well. In the end, we can conclude that the duplication of purchase aligns with the trend of brand penetration as evidenced with the high correlation result.

1.1 Conclusion Summary

To summarize the findings, there is some applicability of the Dirichlet model for the brands without the violence of underlying assumptions. With all the tests, there are the presences of both Double Jeopardy and Duplication of Purchase patterns. This indicates the advantages that large brands do have that emerges from its higher penetrations. For this case specifically, there are the excess behavioral loyalty for two largest brands making their performance distinctive by far. The analysis also showed that all the Dirichlet consumer patterns are visible even the market of FDA category in Bangkok has some deviation on the assumptions as well as being a choice free subscription market.

2. Managerial Implications

2.1 Brands should be careful for their objectives on brand performance measures and benchmarks when the Double Jeopardy pattern occurs in the market

When there is the visibility of the double jeopardy effect in the competitive landscape the brands need to be more cautious about their owned performance in which sometimes the descriptive statistics may not cover because the brand might just perform normally according to its size.

The analysis reveals three primary domains where larger brands can yield greater advantages: purchase frequency, number of total buyers, and excess behavioral loyalty. These benefits contribute to a notable inclination in favor of the brand's performance metrics, such as average purchase frequency, penetration rates, or share of category requirements (SCR). Consequently, larger brands find it comparatively effortless to achieve higher scores in their evaluative benchmarks, a feat that proves more challenging for their smaller counterparts. This phenomenon aligns with the inherent characteristics of the double jeopardy pattern, underscoring that larger brands tend to naturally excel, whereas smaller brands may face disadvantages due to their limited size.

Therefore, adopting the NBD-Dirichlet model is a strategic approach to address these challenges and derive more accurate insights, brands, especially smaller ones, should consider leveraging the Dirichlet model test. By applying this approach to improve a realistic assessment of brand performance and not be discouraged by the punishment from size, larger brands should also be cautious about the source of their superior performance. The Dirichlet model not only facilitates the identification of realistic targets but also aids in understanding market dynamics more holistically.

2.2 The suitable goal for brand growth is to penetrate for a larger customer base but brands need to be cautious with the distributions (physically and mentally).

From 2.1, what becomes the primary objective for businesses to pursue when the loyalty of brands in the same category have quite the same amount of loyalty buyers (except brands with excess behavioral loyalty, it's about distribution). This equivalency in loyalty behavior distribution across the market holds even as penetration rates fluctuate based on individual market shares. Both from existing literature and the findings of this study reinforce the crucial role of penetration in driving brand expansion. The fundamental concept centers on penetrating the market to establish a larger customer base, encompassing consumers of various profiles (light, moderate, heavy, or exclusive buyers), thereby distinguishing it from the conventional approach primarily reliant on sole buyers and their repetitive purchases. In addition, the study also reveals that brands with greater penetration rates would experience a higher proportion of switchers from other brands, aligning with the duplication of purchase law.

2.3 Distribution is one of the important factors leading to excess behavioral loyalty.

This study did not directly assess the excess behavioral loyalty because the concept is beyond the scope of the Dirichlet model itself. However, valuable insights can still be extracted from the existing literature. Research in the field suggests that larger brands often experience higher levels of loyalty due to their superior distribution strategies, which result in wider product availability and heightened customer considerations.

The extensive research by Fader and Schmittlein (1993) offers a further pattern into the phenomenon of double jeopardy as the excess behavioral loyalty (loyalty that gained from market shares premium. They suggest that the pattern of loyalty would occur only when there is market segmentation that comes from the distribution effect. The literature critically examines the NBD-Dirichlet model and emphasizes its limitations as an aggregate model, failing to account for dynamic marketing elements and strategies over time. This underscores the significance of understanding the distribution effect, which plays a crucial role in shaping the unusual loyalty patterns. This study also found the excess behavioral loyalty pattern in the FDA market.

While traditional Fast-Moving Consumer Goods (FMCG) markets may witness distribution advantages for larger brands distributing far greater numbers of physical products to their potential shoppers, the application market's distribution dynamics are distinctive. Users' access to applications is simplified, yet the true distribution occurs upon downloading the application onto their devices, not the availability of the application on the app stores. This highlights a new hypothesis from this research that the downloaded repertoire may heavily influence users' decision-making process within their available set of applications. As popular brands dominate downloads, the concept of mental availability becomes prominent. Users' consideration sets primarily consist of these downloaded options, emphasizing the influence of distribution on customer behavior and loyalty.

Conclusively, the literature highlights that the distribution effect is a key determinant of market partitioning, consequently driving excess behavioral loyalty. For businesses operating in application markets, optimizing distribution strategies becomes crucial. By strategically getting more people to use their app and making it a regular choice for them, smaller brands can steadily grow their presence in the market.

3. Limitations

It is crucial to acknowledge the limitations of the study. Firstly, the convenience sampling method utilized in this research does have inherent flaws. Although it was selected due to time constraints and practicality, it may not fully represent the entire target population, leading to potential biases in the results. Additionally, it's essential to note that the current sample size is relatively small, which could limit the generalizability of the study's findings. Secondly, the survey design used in this study necessitates consumers to recall their purchase behavior. This reliance on memory might introduce recall bias, as respondents may find it challenging to remember their past purchases accurately. Therefore, the observed data period is limited to only one month of purchase occasions because forcing a recall over a period of one month for this type of daily purchased service is impractical. Consequently, the time period of the observation is also the limitation of the research because extending the observation period to cover a longer timeframe, as suggested by existing literature (Goodhardt et al., 1984;

Bennett and Graham, 2011), would allow for a more comprehensive analysis of purchase duplication laws and provide a better understanding of consumer switching behavior.

Given that the existing literature focuses on the model's limitations, specifically its simplification and aggregation of purchase behaviors without accounting for dynamic marketing strategies over time (Driesener & Rungie, 2021; Fader & Schmittlein, 1993), it is important to acknowledge that the model falls short in capturing the impact of marketing efforts and the exact origins of excess behavioral loyalty. As a result, this study primarily relies on insights from Fader and Schmittlein's (1993) literature to analyze excess behavioral loyalty. Nevertheless, it is important to note that this alone may not suffice to definitively attribute the excess behavioral loyalty observed in the Bangkok FDA market solely to the distribution effect, warranting further empirical testing. Lastly, the Dirichlet model does not account for the marketing and promotional attempt with the observation period that may differ the results in a short term.

4. Future Studies

To address concerns regarding the timeframe and precision of the survey design, several strategies can be employed. The first approach involves utilizing Panel data, which enables a more precise understanding of each user's purchasing behavior over an extended duration. The second technique involves requesting respondents to delve into their application history, thereby enhancing accuracy by going beyond approximations of past usage and getting rid of the recall ability bias. However, this method necessitates a substantial budget and time investment due to potential reluctance to participate. A third method, introduced by Bennett and Graham (2010) and applied within the Thai car industry, revolves around a "two purchases analysis." This approach examines the two most recent car purchases to identify instances of switching behavior, aligning well with the analysis of the duplication of purchase law. Lastly, the Juster scale, as proposed in Bergström and Ones (2013), can be employed to estimate and quantify purchase behavior, providing a numerical representation of that behavior but the flaw is that it clings towards the attitudes over the actual behavior.

To uncover the origins of excessive behavioral loyalty, Fader and Schmittlein (1993) introduced a disaggregate model that dissects the phenomenon by applying the Dirichlet assumptions. In upcoming studies, the survey could be enriched with greater detail regarding purchases, brand-related marketing efforts, customer journeys, and psychographic segmentation. This would enable a deeper exploration of the underlying factors that contribute to brand penetration as well as to test the new hypotheses about the distribution emerging from this research. Given the constraints on the current research's timeframe, the examination of Mean Absolute Deviations (MADs) to assess homogeneity within the FDA market was omitted (Kennedy and Ehrenberg, 2000). Consequently, future investigations still offer the opportunity to address this aspect.

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