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Between app efficiency and user wellbeing: a cluster analysis on consumer types and continuance usage of food delivery app

Thu Thi Trinh
Swinburne Vietnam - FPT University, Vietnam
tttrinh@swin.edu.vn

Xuan Tai Mai
Department of Hospitality and Tourism - FPT University, Vietnam
taimx@fe.edu.vn

***Abstract*—The introduction of food delivery apps, facilitated by the global pandemic, has created a significant disruption in the hospitality industry. However, how consumers use mobile applications in the context of daily choices and food consumption has not been fully explored. Using data collected through an online questionnaire comprising 165 food delivery app subscribers, k-mean cluster analysis was performed to classify users based on their internal motivations. The results reveal three distinct groups: Health-conscious Eaters, Food Enthusiasts, and Lifetime Diners. Practically, the present exploratory study assists FDA providers to better identify customers, so potentially optimizing marketing initiatives, and maximizing profitability.**

***Index Terms*—Cluster analysis, Food delivery app, Customer segmentation.**

I. Introduction

Customers can currently access a wide range of services anytime and anywhere with their smartphones and the internet [1]. The growing use of online food delivery apps (FDA), facilitated by the global pandemic, has significantly transformed the food sector [2,3]. FDA is defined as a mobile-based application utilized to contact restaurants, search and order food for delivery, and pay for the bills without physical interaction with restaurant personnel [4]. The worldwide market of FDAs was estimated to achieve turnover of US$ 5,400 million in 2022 and is forecast to increase at a Compound Annual Growth Rate (CAGR) of 12.54% to reach approximately US$ 9.772 million in 2027 [5]. The increasing usage is mainly though due to an adaption to the “new normal” in consumer lifestyles, such as social distancing, contactless delivery, and hectic work schedules [6].

While the FDA witnessed explosive growth during 2020-2021, they are encountering its slowest growth in years in the post-pandemic commencing 2022. The fall in app usage can be explained by the relaxation of stay-at-home restrictions and consumers returning to restaurants to enjoy in-person dining [7]. Equally, the competitive landscape in the market is getting more intense. The major players in the market - Delivery Hero, Just Eat, and Uber Eats – compete intensively to acquire users [8]. Moreover, FDA’s consumers nowadays are becoming less loyal to a single service provider [9]. With an increasing number of FDAs, customers tend to hop between apps to find their best options. Therefore, it is imperative for the providers to understand users’ demands to obtain a sustainable sales performance.

Discovering consumer behaviors offers a better insight into consumer profiles that ultimately provide a solid background for deploying marketing strategies [10]. Consequently, classifications of e-commerce customers are more common. For instance, Chawla and Joshi (2017) divided mobile banking users into three groups based on demographic and behavioral factors [11]. Ariguzo and White (2011) classified mobile commerce users by three variables: gross domestic product per capita, mobile cell phone use, internet use [12]. Neunhoeffer and Teubner (2018) utilized consumer motives to segment consumers in peer-to-peer sharing platforms [13]. Despite the prevalence of FDA, no studies have yet examined consumer segmentation with respect to their behavioral factors in this emerging domain.

Customers can be distinguished according to a general attitude, internal motivations, personal concerns, and demographic elements [13]. In this paper, we identify the primary motivational constructs of FDA users from a sample of 165 survey respondents using items based on perceived ease of app usage and socio-demographic data. The differences between FDAs are thought to be app efficiency, user benefits, and continued behavior. Regarding practical implications, the present study assists FDA providers in better managing customer investments, optimizing marketing initiatives and maximizing profitability.

II. Literature Review

A. Food delivery application

FDA is defined as a mobile-based application utilized to contact restaurants, search and order foods for delivery, and pay for the bills without physical interaction with restaurant staff [4]. Moreover, the app can save consumer information such as recent orders, food preferences, or payment methods to facilitate the next purchase [14]. By using these apps, customers can access and order their meals from various independent restaurants at anytime and anywhere. According to Chen et al. (2020), the FDA is an example of online-to-offline commerce (O2O) that has triggered one significant disruptions in the hospitality sector [14].

FDA can be divided into two classifications [15]. On the one hand, catering services can offer their own FDA, such as Domino’s, Pizza Hut, and KFC. Alternatively, intermediary providers create multi-restaurant platforms, such as Uber Eats in the US, and Meituan Dianping in China. The popularity of FDA has shifted the way people order and consume food on a global scale [16]. It not only helps to facilitate convenient and swift food delivery to the customers’ front door with a few taps of a smartphone screen [6] but also satisfied consumers' demands for personal safety and health concerns [17] during the global pandemic.

B. IT-related motives

The technology, especially the mobile applications, plays a vital role in the food delivery process. Accordingly, information and system qualities are the critical components for IS success that subsequently affect actual usage of IT [18]. Thus, our study employed information quality and system quality as the significant IT-related dimensions that motivate a user to adopt a system. From the user's perspective, information quality is an overall level of assessment that the system is helpful for accomplishing a specific outcome [18]. In the context of e-commerce, DeLone and McLean (2003) indicated that information quality was evaluated based on accuracy, timeliness, completeness, relevance, and consistency [19]. The FDA provides consumers with more comprehensive, up-to-date, and accurate information about restaurants, menus, food descriptions, etc. Accompanying this information is the ability of the FDA to display real-time information for the customer to see their order progress and shipper locations [20].

Moreover, system quality encompasses the characteristics such as ease of use, functionality, reliability, flexibility, portability, and integration [19]. Customers prefer to use a system that can offer the maximum technical efficiency and expected accuracy [21]. Similar to other mobile apps, FDA should provide easy-to-use navigation control that allows users to go to the desired pages easily and quickly within the app. In addition, it also has filter functions for the consumer to sort out foods according to their interest with minimal effort [22]. If the users experience better system performance, it will result in higher usage.

C. User wellbeing and benefit motives

Subjective wellbeing refers to "experiencing happiness, including life satisfaction and positive affect" [23]. Diener, Suh, Lucas, and Smith (1999) indicated that subjective wellbeing is a broad category of phenomena consisting of individuals' emotional responses, domain satisfactions, and global judgments of life satisfaction [24]. Subjective wellbeing is an essential element of positive wellbeing and health [25]. People with a low degree of subjective wellbeing can employ technology to enhance their subjective wellbeing [26]. For example, mobile mindfulness applications, such as Headspace and Calm, support mental health and wellbeing [27]. Apple, Facebook, and Google have introduced a time tracker for their apps so users can see when and how long they spend time on apps and devices [28].

Past studies have concentrated on behavioural factors to classify users into discrete segments in the context of IS [11,13]. On the other hand, other beneficial elements could be significant in the context of food consumption, such as users' overall wellbeing, which has not yet been investigated in the literature in this discipline. In fact, the FDA gets food delivered to customers' front door with a few taps of a smartphone screen [6]; that not only makes people's lives more convenient but also enhances their quality of life [29]. Thus, these benefits permit users gain a higher level of perceived wellbeing through using the app.

III. Methodology

IV. Data collection

Prior to the official data collection, the survey instrument was piloted with 6 FDA users to ensure its clarity and relevance. The pilot study indicated that the respondents clearly understood the questions and items. For the final data collection, the study employed an online questionnaire using Google Forms, and data was gathered via the Prolific platform.

As the study targets consumers who are using FDA, we utilized the Prolific advanced feature to recruit FDA subscribers from over the world. We double-checked the respondents by asking filter questions "Do you currently use any food delivery app?" and the follow-up question "Please name the food delivery app that you use most frequently". Participants were initially informed the purpose of this research and the protocol in the first section of the survey in compliance with ethics requirements. A total of 165 valid responses were selected for further analysis.

A. Measurement

All the questionnaire items in this study were adapted from studies of information systems, and revised for the research context of the FDA. The app-related factors, including system quality and information quality, were adapted from [30, 31]. Subjective wellbeing was measured by four items by [32, 33]. Continued usage was developed based on [4, 31]. All items were measured by seven-point Likert scales, ranging from strongly disagree (1) to strongly agree (7). The third section contained demographic questions (age, gender, education) and FDA usage behaviors (usage frequency, usage experience, and frequently ordered items on FDA). Table 1 describes the nature of the sample.

TABLE I. DESCRIPTIVE ANALYSIS

Variable	Category	Frequency	Percent (%)
Usage Experience	Under 1 year	30	18.2
	From 1 to 3 years	92	55.8
	From 3 to 5 years	34	20.6
	Over 5 years	9	5.5
Usage Frequency	1-5 times	118	71.5
	6-10 times	39	23.6
	11-20 times	7	4.2
	More than 20 times	1	0.6
Gender	Male	77	46.7
	Female	88	53.3
Age	Under 20 years old	4	2.4
	From 20 to 30 years old	121	73.3
	From 31 to 40 years old	24	14.5
	41 years and older	16	9.7
Education	High school or equilvalent	26	15.8
	Vocational/ technical school	1	0.6
	Some College	40	24.2
	Bachelor's Degree	71	43
	Master or Higher Degree	27	16.4

TABLE II. FREQUENTLY-ORDERING ITEMS ON FDA

Classification	Count	% of respondents
Fast foods	159	96%
Speciality foods	47	28%
Diet foods	5	3%
Drinks	35	21%
Desserts	14	8%

B. Data analysis

1) Factor analysis and reliability test

The collected data were analyzed using SPSS 25.0 version. In the first step, we utilized exploratory factor analysis (EFA) for 16 items of total variables. Table 3 shows the results of varimax rotation with a reduced set of 13 items. Three factors were obtained with factor loadings above a critical value of 0.5. It is important to note that items "Using this app met your overall need for wellbeing", "Assuming you want to order meals, you intend to use this app" and "If you have an opportunity, you will order meals through this app," reported cross-loadings between factors and were then removed. As presented in Table 1, three factors were labeled based on the item characteristics. Factor 1, "App Efficiency," was based on the app functions and benefits, with factor loadings greater than 0.723. Factor 2, "User Wellbeing", was related to the usage purposes and consequences, with factor loadings greater than 0.836. Factor 3, "Continued Behavior," indicated the usage behavior, with factor loadings greater than 0.834. The reliability Alpha values for "App Efficiency", "User Wellbeing" and "Continued Behavior" were 0.921, 0.88, and 0.718, respectively.

TABLE III. FACTOR ANALYSIS AND RELIABILITY ANALYSIS

Construct	Items	Factor Loading	CA
App Efficiency	This app is user friendly	0.855	0.921
	This app is easy to use	0.818	
	This app provides you with sufficient information	0.805	
	The information content meets your needs	0.796	
	This app provides precise information you need	0.793	
	This app has high efficiency	0.793	
	This app has high reliability without errors	0.745	
	This app provides up-to-date information	0.723	
User Wellbeing	Your life is excellent when you use this app.	0.906	0.88
	You are satisfied with your life when you are using this app	0.896	
	Using this app played an important role in enhancing your quality of life	0.836	
Continued Behavior	You will keep ordering food through this app rather than to use any alternatives in the future	0.866	0.718
	You will continue to use this app in the future	0.834	

2) Cluster analysis

Next, a K-means nonhierarchical cluster analysis was used to segment users into groups. This method minimizes within-cluster distances and maximizes between-cluster distances until a point till final cluster centers are identified [11]. Initially, we determined the exact number of clusters (k) by using a k-mean clustering validation for k=2,3,4. The iteration data revealed that the final cluster centers with the maximum absolute coordinate change for any centers is .000 at the current iteration 8 for k=2 and k=3 (see Table 4). However, due to the lower exploratory power of k=2 [13] and for the nature of this exploratory study, we selected k=3 for final number of cases for further analysis.

TABLE IV. ITERATION HISTORY (K=3)

Iteration	Change in Cluster Centers		
	1	2	3
1	2.431	3.259	3.422
2	0.681	0.156	0.488
3	0.326	0.118	0.208
4	0.000	0.098	0.175
5	0.000	0.092	0.139
6	0.000	0.116	0.147
7	0.000	0.060	0.077
8	0.000	0.000	0.000

The one-way ANOVA results in Table 5 reveal that all the variables of Usage Experience (F=20.913, p=0.000), Usage Frequency (F=20.743, p=0.000), App Efficiency (F=115.835, p=0.000), User Wellbeing (F=40.788, p=0.000), and Continued Behavior (F=37.012, p=0.000) are significantly in forming the cluster. This indicates that among the three clusters created, there are significant differences in the above dimensions. Moreover, cluster 1 consists of 6 respondents, cluster 2 consists of 90 respondents, and cluster 3 has 69 respondents as presented in Table 6.

TABLE V. ONE WAY ANOVA RESULTS

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Z-score: Usage Experience	16.827	2	0.805	162	20.913	0.000
Z-score: Usage Frequency	16.718	2	0.806	162	20.743	0.000
Z-score: App Efficiency	48.256	2	0.417	162	115.835	0.000
Z-score: User Wellbeing	27.462	2	0.673	162	40.788	0.000
Z-score: Continued Behavior	25.717	2	0.695	162	37.012	0.000

TABLE VI. THE NUMBER OF CASES IN EACH CLUSTER

Cluster	Number of Cases in each Cluster	Percentage
1	6	3%
2	90	55%
3	69	42%
Total	165	100%

3) Cluster description

In the following, we describe each cluster and name them according to their characteristics. Table 7 presents the mean comparison of each construct among segmentation. Figure 1 illustrates the comparison of different dimensions among clusters.

Cluster 1: Heath-conscious Eaters

The number of members in this cluster is the smallest (n=6). Users in this cluster care more about their subjective wellbeing while using FDA (M=4.722). However, this group had the lowest mean scores for other elements, including App Efficiency (M=2.8542), and Continued Behavior (M=4.6667). Members of this group have an average experience of using FDA (M=2.17) and are potentially regular customers (M=1.17). Thus, these consumers are named "Health-conscious Eaters", who take their wellbeing into consideration when ordering meals via FDA.

Cluster 2: Food Enthusiasts

The number of members of this cluster is the largest of all clusters (90 people out of 165). Users included in this segment was characterized by a high expectation for app efficiency (M=5.6736) and high continuance usage (M=5.2722). They are also less concerned with their wellbeing (M=4.0556). Consumers in this group show the lowest scores regarding both usage experience (M=1.82) and usage rates of FDA (M=1.11). Due to participants seemingly value the effectiveness and efficiency of FDA service, users in cluster 2 are labeled "Food Enthusiasts".

Cluster 3: Lifetime Diners

Cluster 3 contained 42 percent of participants (n=69). Compared to the other two clusters, consumers in this cluster have the highest score for all dimensions. They have the highest interest in app efficiency (M=6.3134). They tend to care extra about their wellbeing when ordering meals via FDA (M=5.5556) and are more likely to continue using FDA (M=6.3116). Consumers in this group order more frequently (M=1.65) and have extensive experience with FDA (M=2.54). We name this cluster "Lifetime Diners", who are demanding and probably high-value customers for FDA in the long term.

Table VII. Mean Comparison Among Clusters

	Cluster 1 (n=6)		**Cluster 2 (n=90)**		**Cluster 3 (n=69)**	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
App Efficiency	2.8542	1.3215	5.6736	0.54137	6.3134	0.47192
User Wellbeing	4.7222	0.68041	4.0556	1.16036	5.5556	0.87758
Continued Behavior	4.6667	1.25167	5.2722	0.89053	6.3116	0.64227
Usage Experience	2.17	0.753	1.82	0.68	2.54	0.698
Usage Frequency	1.17	0.408	1.11	0.35	1.65	0.703

In addition, the chi-square test was performed to examine whether the demographic variables were statistically significant across the three proposed clusters (see Table 8). Neither gender nor age were discriminating variables. On the other hand, the chi-square statistical test of the univariate multinomial model suggests a significant relationship between education level and the group (Wald = 34.093, d.f. 8; p<0.001). We are more likely to find those having a bachelor's degree

Fig. 1 Comparison among cluster

in cluster 2 (27% of total respondents), although a higher percentage of consumers having both a bachelor and higher degrees are found in cluster 3 (30% of total respondents).

Table VIII. Distribution of Respondents Per Cluster According to Demographic Variables

Demographic characteristic of clusters			**Cluster 1**	**Cluster 2**	**Cluster 3**	**Chi-square test**
Gender	Male	Count	3	45	29	Chi-square (2)=1.025, p=0.599
		%	1.80%	27.30%	17.60 %	
	Female	Count	3	45	40	
		%	1.80%	27.30%	24.20 %	
Age	Under 20 years old	Count	0	1	3	Chi-square (6)=3.474, p=0.747
		%	0.00%	0.60%	1.80%	
	From 20 to 30 years old	Count	4	70	47	
		%	2.40%	42.40%	28.50 %	
	From 31-40 year old	Count	1	12	11	
		%	0.60%	7.30%	6.70%	
	41 years and older	Count	1	7	8	
		%	0.60%	4.20%	4.80%	
Education	High school or equilvalent	Count	1	16	9	Chi-square (8)=34.093, p=0.000
		%	0.60%	9.70%	5.50%	
	Vocational/ technical school	Count	1	0	0	
		%	0.60%	0.00%	0.00%	
	Some College	Count	1	28	11	
		%	0.60%	17.00%	6.70%	
	Bachelor's Degree	Count	2	32	37	
		%	1.20%	19.40%	22.40 %	
	Master or Higher Degree	Count	1	14	12	
		%	0.60%	8.50%	7.30%	

4) Validation of clusters: multiple discriminant analysis

To further validate the clusters, we conducted a multiple discriminant analysis. The results are illustrated in Table 9. Firstly, there are two discriminant dimensions, both of which were statistically significant by the chi-square test (p<0.001). The canonical correlations for functions 1 and 2 are 0.848 and 0.635, respectively, which suggested a relatively high level of relationship between the discriminant scores and the groups. Table 9 also indicated that besides app efficiency, function 1 imputes importance to other usage behavioral factors, whereas function 2 emphasizers user wellbeing. Moreover, 98.2% of the participants were accurately allocated to the cluster grouping. Figure 2 shows canonical discriminant functions that visualize the differences among clusters.

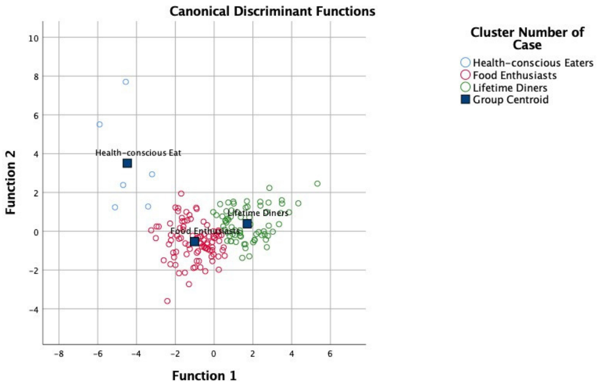

Fig. 2 Canonical discriminant functions

TABLE IX. SUMMARY OF MULTIPLE DISCRIMINANT ANALYSIS

Testing Significance of Three Clusters

Function	Canonical Correlation	Wilks' Lambda	Chi-square	Sig.
1	0.848	0.168	285.79	0.000
2	0.635	0.596	82.723	0.000

Standardized Canonical Discriminant Function Coefficients

	Function 1	Function 2
Zscore: Usage Experience	0.435	0.384
Zscore: Usage Frequency	0.415	0.195
Zscore: App Efficiency	0.711	-0.704
Zscore: User Wellbeing	0.326	0.616
Zscore: Continued Behavior	0.436	0.191

Classification Results

Cluster Number of Case			Predicted Group Membership			Total
			Health-conscious Eaters	Fo	Lifetime Diners	
Original	Count (%)	Health-conscious Eaters	5 (83.3%)	1	0	6
		Food Enthusiasts	0	90	0	90
		Lifetime Diners	0	2	67 (97.1 %)	69

Note: 98.2% of original grouped cases correctly classified.

V. DISCUSSION

The aim of this research is to define and demonstrate segments of users who are using the FDA in their daily lives. Though consumers' motivational factors, namely app efficiency, user wellbeing, and continuance intention, this study grouped users into four unique segments: Health-conscious Eaters, Food Enthusiasts, and Lifetime Diners.

A large number of users – Food Enthusiasts - were characterized as having an interest in app-related features that provide them with functional values, such as easy-to-use navigation control and accurate information. This group of users has slightly favorable motivations toward their wellbeing state. They also rarely utilized FDA for ordering meals (around one to five times per month). However, these individuals showed a high stickiness toward the use of the FDA. Therefore, to increase the retention of this segment, FDA should provide practical or price value to help them save time or money.

The study also reported a small potential group fond of healthy food to enhance their subjective wellbeing – Health-conscious Eaters. Remarkably, the low continuous intention was reported in these users despite their moderate purchase frequency. We propose the app should add more healthy food options, nutrition descriptions, or wellbeing-oriented activities within the app (e.g., counting food calories, mindful eating exercises) to encourage the continuance usage of this emerging group.

Our findings suggested the highly profitable consumer segment for FDA: Lifetime Diners. These participants were described as highly-favorable motivations toward app efficiency and their subjective wellbeing. They may perceive FDA as being easy to use, functionality, portability, and wellbeing assistance. This segment is ideal for FDA providers to interweave technological-related values with health-focused features that help them achieve a state of wellbeing.

With regard to theoretical contributions, this paper is among the first in the academic literature to examine the customer segmentation of the FDA. We shed light on possible consumer classifications and the differences in behaviors among these segments on the FDA. Our findings enrich the knowledge of consumer characteristics in the use of information systems in general and the online delivery platform in particular. From a practical perspective, this paper suggested the three distinguished customer segments for FDA providers: Food Enthusiasts, Health-conscious Eaters, and Lifetime Diners. Thus, marketing strategies (including feature development and target promotion) should deal with the variety of needs and motives of consumers, depending on specific segment, to target consumer more effectively, which ultimately increases consumer purchase intention.

VI. CONCLUSIONS AND FUTURE RESEARCH

Food delivery service has become increasingly an integral part of everyday lives. Despite the rapid rise of this technology, little remains known in terms of user typologies and their related motivational factors. This study has revealed that FDA users are not homogenous but rather heterogenous in their using motives. The first group, Health-conscious Eaters as we name them, are those who use apps to support their wellbeing goals. The second group, Food Enthusiasts, includes individuals who show a high engagement with app technology. Finally, the third group, Lifetime Diners, who strongly demand for both utilitarian and hedonic value of the app. For practical implications, the results from this study may assist FDA providers in better managing customer investments and optimizing retention strategies for sustainable profitability.

Further research is also required to enrich our understanding of the segments, especially niche markets. Finch (2019) indicated that the K-mean algorithm tends to allocate most members of the sample into the group related to the largest cluster, which may result in a concern in practice when the small group represents a rare but significant subgroup [34]. Indeed, our results revealed a small number of users classified in a Health-conscious Eaters segment. It also aligns with our findings in Table 2 that 96% of respondents ordered fast foods while only 3% mentioned ordering diet foods on the FDA. The demand for mindful eating is obvious [35]. Therefore, further exploration should examine with a larger sample size to analyze this potential subgroup.

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