JOHAR – Journal of Hospitality Application & Research
17 (1) 2022, 19-34
http://www.publishingindia.com/johar/

AN APPLIED RESEARCH INTO UNDERSTANDING HOW SOCIO-DEMOGRAPHIC FACTORS AFFECT THE EATING OF OUTSIDE FOOD FOR URBAN POPULATION

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Abstract

Purpose/Aim – This article aims at analyzing the consumers' eating out habits and preferences as to restaurant service attributes and factors affecting eating out, through a primary survey of 193 urban respondents who were interviewed through a structured questionnaire. For leveraging consumer insight about eating outside food, and to understand how socio-demographic factors affecting eating outside food are important to the restaurant industry for developing strategies to attract potential consumers in order to tap the emerging market potential. Eating of outside food corresponds to both dining out as well as ordering through food apps. The study also investigates how the COVID pandemic has affected the consumption of outside food.

Design/Methodology/Approach – A survey was initiated, and data collected from 193 respondents across urban areas. A convenient sampling was used for the purpose. A Random Forest was used to find the key socio-demographic factors influencing the eating of outside food. Paired t-test to test differences between pre-COVID and the current situation for dine out as well as ordering through apps was conducted. The analysis was conducted in R studio.

Findings – The study finds there is significant difference in eating of outside food (both through apps as well as dine out) between pre-COVID times and the current situation. It also finds that family type, education, annual income and occupation are significant factors in the ordering of food through food apps and age is found to be a significant factor where people prefer to dine out.

Research Limitations – The study was conducted in India and this study can be replicated in the adoption of food apps in other countries as well. Important constructs like personal innovativeness, network effects and habit are not yet studied. Sample size should have been larger and wider for better explanatory power. Explanatory power will be high when we include behavioural constructs along with the socio-demographic variables.

Practical Implications – Food tech companies can make a segmented marketing approach using this research. The study results provide practical implications for the Indian restaurant and food tech industry. It provides strategic inputs to the food tech industry for developing effective strategies as per consumers socio-demographic attributes. Restaurants also can use this report to get insight into their customers. Restaurants can customize menu according to different socio-demographics.

Originality/Value – There has been no research conducted in understanding how socio-demographic factors affect the app usage as well as dining out during the context of COVID. Previous research studies have not looked into the family type, Occupation type, Sector in which the person works and the type of housing. A Random Forest model would provide us with key significant socio-demographic variables and hence this study could be used.

Keywords: *Dine Out, Outside Food, Food App, COVID, Paired T-Test*

Introduction

Mobile food ordering apps have become ubiquitous in India. If you cross through the Tier 1 and Tier 2 towns of India it is highly likely that you see people with Swiggy and Zomato drivers crisscrossing the lanes on their two wheelers. Mobile food-ordering apps are here to stay in the food service industry and their popularity is only expected to grow in the coming years. With the current scenario of double income families, convenience factors due to traffic, pandemic situation and better connectivity and affordable smartphones, food ordering apps are definitely here to stay. The increase in family incomes, changing lifestyles and eating patterns have led to an increase in market growth. The demand for food apps is growing coupled with affordable prices and this has led to the growth of the business (Business Insider, 2020). The average order value on food delivery platforms was about Rs 320 pre-COVID-19 and has since increased to Rs 420 (Economic Times, 2020).

The report by Google and Boston Consulting Group has revealed that variety in cuisines was the most important factor in the adoption of the food apps, followed by good discounts and convenience (Google BCG Report, 2020). Food tech is present in more than 500 cities in India. The major drivers of growth are affordable smartphones, better network connectivity, traffic congestion, and the convenience factor. Network adequacy played a major role in the adoption of apps (52%) followed by advertisements (19%) (Google, BCG; 2020). Indians generally prefer to eat home-cooked meals—a concept supported socially, culturally, and religiously, as well as individually, where female members generally prepare food for the whole family (Goyal & Singh, 2007). Socio-demographic trends are frequently cited as the potential causes of food intake away from home (Nayga & Capps, 1993; Pratten, 2004; Stewart, Blisard, Jolliffe & Bhuyan, 2005). Common socio-demographic factors reported are age, education, income, employment status, household size, and urbanization (Byrne, Capps & Saha, 1996; Marsh et al., 2003).

The food-tech industry in India was valued at US $5bn. in 2020 and the valuation is likely to increase to US $8bn. in 2022 with a CAGR of 30% (Google BCG Report). The food delivery app market is in a kind of duopoly with Zomato and Swiggy ruling the space. They are currently present in around 500 cities in India. The amount of capital infused in 2018 in the food-tech business in India was US $480mil., which was more than triple the inflows of US $135mil. in 2017 (Bhattacharya, 2018). Swiggy received the highest infusion of US $100mil. among the incumbents (Kashyap, 2018). Mergers and acquisitions dominated the industry as consolidation and size were the buzzwords (Sinha, 2019).

The industry report expects factors like changing demographics, increase in disposable income, growing urbanisation, internet penetration and proliferation of online services to accelerate the growth of the industry. IFSR 2019 puts the share of the organised industry in the overall Food Services industry stake at 35%. The share of the organised industry is expected to reach 43% in the next five years. The industry employs 7.3 million people as of today and is expected to increase to 9.2 million in 2022-23. Zomato acquired Uber Eats for about US $ 350mil. in the year 2019.

Business models used by the firms is the intermediating platform model. Swiggy and Zomato have a presence in around 500 cities. After three to four years of mounting losses, the recent trend in the industry has been that of consolidation and profitability measures.

Literature Review

In a study done by Delians et al. (2014) which focussed on eating behaviours of college students, easiness and convenience were presented as important factors in eating decisions due to limited time. Taylor (2020) conducted a study on students' intentions to use a food ordering app. The study uses UTAUT model to assess the importance of six key determinants like performance expectancy, effort expectancy, risk perceptions, hedonic motivation, trust and social influence.

Annaraud et al. (2020) made a study on what drives satisfaction and, in turn, the intention to use food delivery apps. This study proposes how convenience, control, customer service and fulfilment and food quality improves the satisfaction and which in turn influences the intention to use. It was also found that convenience was not a major factor in determining satisfaction in food delivery apps.

A study was conducted by Samala (2018) to understand the important factors which influence the usage of the mobile app. They were found to be ease of use, convenience, promotions and coupons, speed of delivery, no time for cooking and variety of food. Byrne, Capps and Saha (1998) used Probit analysis to examine the factors affecting the probability of dining out and regression analyses to examine expenditure by type of food service facility.

Kim and Gesitfield (2003) conducted a study on what kind of customers would choose a specific type of restaurant - full service restaurant, quick service restaurant, retail food establishment and other commercial food establishments. They used multinomial regression based on the socio -demographic factors to understand how it influences the choice of restaurant customers go to.

Kapoor and Vij (2018) made a study on the mobile app attributes which enhance conversion. The attributes were information design, navigational design, collaboration design and visual design. The participants were undergraduate students from Delhi University.

Chow et al. (2017) examined the structural relationship between convenience motivation, post-usage usefulness, hedonic motivation, price saving orientation, time saving orientation, prior online purchase experience, consumer attitude and behavioural intention towards OFD services.

This article aims at understanding the key socio-demographic factors which influence the eating of outside food. The article uses Random Forest to develop a model for predicting the frequency of eating outside food. The article looks into the significant demographic variables which impact eating outside food. The article also compares dining out and ordering through food apps during the current period and pre-COVID times. There has been no research conducted in understanding how socio-demographic factors affect app usage as well as dining-out preferences. Previous research studies have not looked into the family type, occupation type, the sector in which the person works and at the type of housing in use. This is the research gap this study aims to address. A paired t test is used for comparing the means. Following are the research questions this study aims to address.

RQ1: What are the important socio-demographic variables during this pandemic?

RQ2: Is there a significant difference between pre-COVID period and post-COVID period in terms of the usage of food apps and dining out?

Based on the research questions, the following research objectives are defined:

- To find if there is a significant difference in dine out and app usage frequency before and after COVID.
- To investigate the significance of socio-demographic factors in the frequency of dine out and app usage.

Data and Methodology

Research Instrument

The study is based on a consumer survey conducted using an online questionnaire through google forms. 209 respondents from urban areas like Kochi, Trivandrum, Chennai, Bangalore, Delhi, Mumbai and Kolkata were selected for the purpose. The number of respondents were pruned to about 193 respondents after removing 16 respondents. Out of the 193 respondents, 44 were administered the question in person. The questionnaire was designed in a way as to obtain information about the socio-demographic factors which affect dining out and ordering food through apps. The study was done in the period of November-December 2020 in India when restrictions were lifted in most of the sectors.

There were about a total of 20 questions and the questionnaire was designed to be ideally completed in a minute. Concise and simple questions were asked to ensure that the respondents were able to easily fill the questionnaire in all sincerity. The sampling technique used was snowball sampling.

The Data Analysis is done in R Studio. The Function used is the IM function. R Studio enables us to do the analysis without the need for coding as in SPSS. It automatically takes the categorical variables to be factors. Both Random Forest as well as T-test is conducted in R Studio.

Variable Selection and Description

The Variable selection is done after a focus group discussion with the users of the food app and observations of colleagues and friends.

The dependent variable is a discrete variable which measures the frequency of dining out and ordering through food apps during current circumstances and pre-COVID times. The independent variables are the socio-demographic variables listed above.

Variable	Code	Type	Definition
Gender	GEN	Categorical	Male or Female at two factor levels.
Age	AGE	Categorical	21-30, 31-40, 41-50, 51 & above at four factor levels.
Family Type	FT	Categorical	Bachelor (Either single or living as Bachelor). Nuclear family.
			Without kids (only husband and wife). Nuclear family.
			(husband, wife & children). Extended family which includes.
			Three generations. Joint family includes families where even father's/ mother's siblings also stay together. 5 factor levels are taken for the purpose.
Housing Type	HT	Categorical	Flat/Apartments and Individual houses.
Occupation	OCCU	Categorical	Government, Private, self-employed and students at 4 factor levels.
Spouse Working	SW	Categorical	Whether spouse is working or not and not applicable at 3 factor levels.

Variable	Code	Type	Definition
Annual Income	AI	Categorical	<3L, Not Applicable, 3L to 8L and >8L at 4 factor levels.
Food Type	FOT	Categorical	Veg or Veg/Non-Veg at 2 factor levels.
Dine out	DOBC	Discrete	Frequency of dining out before COVID.
Order through App	FABC	Discrete	Frequency of using food app ordering before COVID.
Dine out Post-COVID	DOAC	Discrete	Frequency of dining out after COVID.
Order through App Post-COVID	FAAC	Discrete	Frequency of ordering through food app post COVID.

Data and Methodology

An empirical model is developed to find the relation between socio-demographic variables and the frequency of eating outside food. In this study, this frequency is calculated for Pre-COVID and Post-COVID situations. The following questions were asked to the respondents apart from the socio-demographic variables which are collected for each respondent.

- How frequently do you order per month using food app? (Pre-COVID period)
- How frequently do you dine out per month using food app? (Pre-COVID period)
- How frequently do you order per month using food app? (Under current situation of pandemic)
- How frequently do you dine out per month? (Under current situation of pandemic)

The dependent variable frequency is a discrete variable and the independent variables are all categorical variables. Random Forest method is used to find the most important variables. Random Forest is used because it is more accurate as well as the problem of scaling the variables is not needed here.

The collected data is coded in excel and converted into a csv file. The csv file is then read into R Studio. The data analysis and descriptive statistics are done using R Studio.

Before/After Effect of COVID Pandemic

The before/after effect of COVID pandemic is measured using a paired t test. The dining out and app usage frequency before COVID and after COVID is measured. Following are the hypotheses.

H11a: There is significant difference in the dining out frequency before and after COVID Pandemic.

H12a: There is significant difference in the app usage frequency before and after COVID Pandemic.

Results and Discussions

Before/After Effect of COVID Pandemic on Dining Out

A paired t test was conducted in R Studio to estimate the differences in the frequency of dining out pre and post-COVID scenarios.

Following is the output of the result on dining out frequency before and after COVID.

```
> t.test(sefa$DO,sefa$DOPC, data = sefa, paired = TRUE)

        Paired t-test

data:  sefa$DO and sefa$DOPC
t = 8.9963, df = 192, p-value = 2.26e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 2.168311 3.386093
sample estimates:
mean of the differences
               2.777202
```

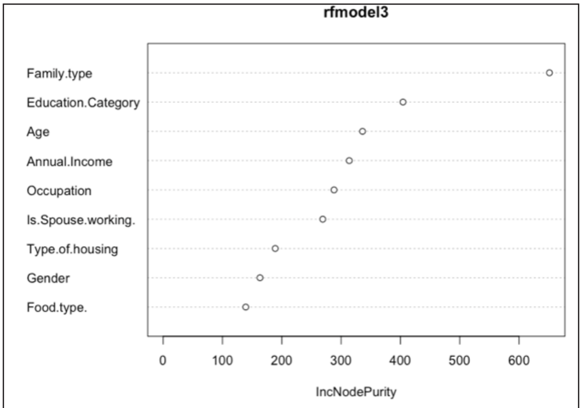
It has been found that the difference is significant. The difference has been significant at 5% significance level. The P value is also less than 0.05. There is an average of reduction of 2.77 times in a month per family in case of dining out when compared to pre-pandemic days. Customers are afraid to go about as there is a risk of exposure. This result has been on expected lines and main objective was to find out the difference in their frequency of going out.

Before/After Effect of Pandemic on Food App Usage

A paired t test was conducted in R Studio to estimate the differences on the frequency of ordering through app pre and post-COVID scenarios.

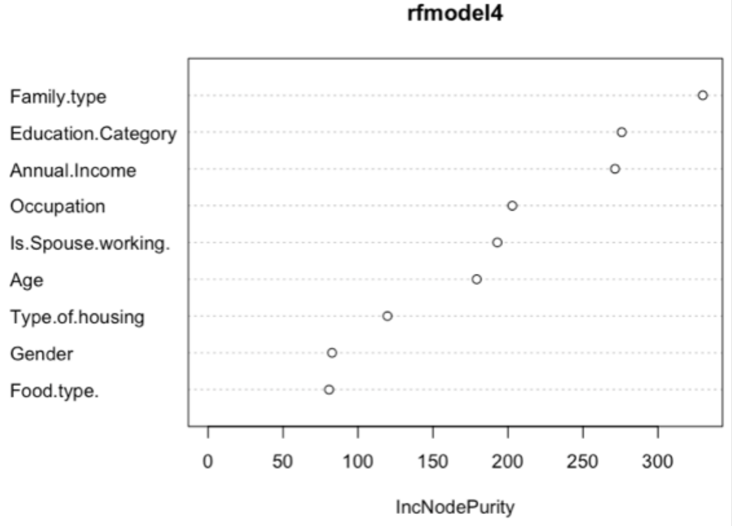
```
> t.test(sefa$OTA,sefa$OTAPC, data = sefa, paired = TRUE)

	Paired t-test

data:  sefa$OTA and sefa$OTAPC
t = 3.2706, df = 192, p-value = 0.001272
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.3527158 1.4244863
sample estimates:
mean of the differences
               0.888601
```

As we can see here, there is a reduction in customers ordering through apps by 0.88 times per month. The difference has been significant at 5% significance level. The P value is also less than 0.05. The major reason is many of the employees work from home and hence there is a tendency to order less through the apps. Although many respondents started ordering instead of going to the restaurant, being home outweighed the average and hence the reduction in the ordering of food through apps. However, the difference is only 1 order per month. Since the earlier average frequency is small, this difference looks significant.




```
                     Overall
Age                 336.1317
Gender              163.2735
Occupation          288.0735
Type.of.housing     188.9811
Family.type         651.2272
Is.Spouse.working.  269.0800
Education.Category  404.3952
Annual.Income       313.6889
Food.type.          139.2927
```

Random Forest - Dining out (After COVID)



	Overall
Age	179.13459
Gender	82.65976
Occupation	202.87444
Type.of.housing	119.61293
Family.type	329.91705
Is.Spouse.working.	192.91174
Education.Category	275.86068
Annual.Income	271.38726
Food.type.	80.68650

Discussion and Key Insights

Gender, food type and type of housing was found to be the variables having the least weightage in both dine out as well as using food apps. Compared to dine out, the significance of these variables is relatively less in the case of food apps as in ordering food at home. This is because age is not a significant variable in ordering through apps. However, the number of dine outs is more for young people.

The family type variable was found to be extremely high for dining out. The reason is because bachelors and nuclear families without kids tend to go out more frequently when compared to joint and extended families. However, in the case of using food apps, the family type is not relatively significant as all types of family order food through apps especially during the prevailing COVID-19 pandemic.

Men go out much more than women. But the gender difference is quite reduced when ordering through food apps. The impurity was about 163 during dine out, however it was reduced to just 82 in case of ordering through apps.

Food type was found to be insignificant for both dine out as well as ordering through apps. However, the importance was higher in terms of dine out as the variety in non-veg is more in Kerala and majority of the population is non vegetarian.

Type of housing was found to be insignificant in both app adoption as well as dine out.

Spouse working was found to be fairly important in the usage of app or dine out. If the spouse is not working, there is a good chance that the consumption of outside food is avoided as the spouse will take care of the household chores which includes cooking. However, we can observe the weightage is more in dine out, as couples have lunch after office hours on the way home. In other cases, one of them has to go home and pick up the other and then go to dine out.

Education, occupation and annual income has been found to be extremely significant in both dine out as well as usage of food apps. There is a very high correlation between education and annual income and hence the explanation for all these two variables are taken together. A person with high income goes to dine out more often as well as orders food from apps more often. People with low income will tend to make their own food and the frequency of dine out will be very less. However, their significance becomes lesser in ordering through apps because the people with high income are going to order dishes in the same price range as that of people with low income as there is no service aspect involved.

Occupation is found to be significant in both dine out as well as through using food apps. It has been observed from the data collected that private professionals dine out the most, followed by government servants, and lastly followed by those who are self-employed.

Managerial Implications

The research will provide critical insights into how socio-demographic characteristics affect the usage of apps and dining out. Restaurants as well as food tech companies can make a segmented marketing approach by looking into the same. It also provides the companies data on the pre-COVID and post-COVID scenarios in terms of eating out and ordering food through food apps. The results of the study provide practical implications for the Indian restaurant and food tech industry. It provides strategic inputs to the food tech industry for developing effective strategies as per consumers socio-demographic attributes. Restaurants can also use this report to get insights into their customers. They can customize their menu according to different socio-demographics.

Recommendations

Family size offers can be made for people with extended and joint families so that they get value for money. Special business lunch can be provided for families with spouse also working as well as self-employed professionals who tend to order less through apps.

Special organic and diet oriented customized food can be provided for people in the age group of 40 and above as this can stimulate sales in that particular segment which is quite untapped. A special dietician and health care specialist can also be added to cater to the segment.

Monthly subscription can be added to target bachelors which can help the food companies increase their cashflow and add value for the buyer. This should be on the lines of the dabbawallas of Mumbai.

Restaurants can customize their menus as dine out is drastically reduced as per the study. They can tie up with food aggregators to offer customized food to different socio-demographic categories.

Limitations and Scope for Further Research

The research was done in India and can be replicated in different geographies to see how the socio-economic attributes will influence dining out preferences and the usage of food apps. This can be done using Hofstede's Culture as a moderating variable to find how it impacts the relationship between socio-demographic factors and the frequency of usage of food apps and the frequency of dining out.

This model should be integrated with technology adoption models like TAM (Davis,1989), UTAUT (Venkatesh, 2003) to come up with an extensive framework for the adoption of food apps. Snowball sampling has been used for this purpose and hence there is a chance that the overall demographic profile can be skewed. Location as a variable has not been taken into consideration. It would be interesting to see if there are clear insights coming because of specific locations. There is also a chance of error from the respondents because of inaccurately mentioning the frequency. This can be verified from their order history from either the Swiggy or Zomato app. The model could be validated if there are around 1000-1500 responses and there are sufficient number of respondents in every socio-demographic category. For example, in the current study, the respondents in the 41 and above age group are less than 30. This can result in a skewed response. Hence, the socio-demographic research could be done in a largescale sample study which includes a sufficient number of every socio-economic indicator. There is a clear need for behavioural constructs in this adoption and this can be done using Technology Acceptance Models. However, the significant socio-demographic variables can be used as a control or moderating variable in technology acceptance models like TAM (1989), UTAUT (2003, Diffusion Theory) etc.

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