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The Classification of Consumer Spending on OFD Platforms using Behavior Analysis

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Abstract. *This study investigated a problem associated with the COVID-19 pandemic, which caused Indonesia to enter an economic recession in the second and third quarters of 2020. In particular, the MSME industry was most greatly affected by the recession (LIPI, 2020). As a result of the pandemic, people were forced to conduct activities online in order to minimize the spread of the virus. Data from the Economic Creative Agency show that 60% of culinary MSMEs in Indonesia were adversely affected by the COVID-19 pandemic. In addition, the high competition among merchants, especially those in the culinary MSME sector, has forced businesses to transform and adapt to the changing situation. Ever since the COVID-19 pandemic, Online Food Delivery (OFD) platforms have become increasingly popular among the public. Thus, in order for MSMEs to continue innovating to maintain the stability of their business, this study uses behavior analysis to identify and segment consumers using OFD services. This study surveyed 100 OFD consumers in Jakarta using a questionnaire. The data were then analyzed using a decision tree model. The results revealed that there were five variables that greatly influenced an OFD consumer's spending: willingness to pay, purchase frequency, region of residence, factors that affect their preferred choice of merchant, and the type of merchant. The optimal decision tree model classified OFD consumer behavior into seven nodes, each with unique characteristics. These results helped to characterize and classify OFD consumer behaviors, allowing restaurants to maintain the profitability of their business by utilizing this information to better understand consumer needs as well as improve their decision-making processes.*

Keywords: *Behavior, business transformation, consumer, online food delivery (ofd), decision tree*

Abstrak. *Penelitian ini dilakukan untuk menganalisa permasalahan yang bersumber dari pandemi Covid-19 yang menyebabkan Indonesia mengalami resesi ekonomi pada kuartal kedua dan ketiga tahun 2020 yang membuat industri UKM terkena dampak terbesar selama pandemi (LIPI, 2020). Sehingga masyarakat melakukan aktivitas secara online guna meminimalisir penyebaran virus. Berdasarkan data Badan Ekonomi Kreatif, 60% UMKM kuliner di Indonesia terdampak pandemi covid. Selain itu, tingginya persaingan antar pedagang khususnya di bidang kuliner menjadikan mereka umumnya tergolong UMKM dan diharapkan mampu beradaptasi dengan keadaan tersebut dengan melakukan transformasi bisnis. Sejak pandemi Covid-19 platform yang digunakan konsumen dalam memesan platform Online Food Delivery (OFD) juga semakin populer di masyarakat. Sehingga inovasi berkelanjutan dari UMKM mendesak untuk dilakukan dan selanjutnya untuk menjaga stabilitas, informasi tentang analisis perilaku dapat membantu mengidentifikasi segmentasi konsumen yang menggunakan layanan OFD. Pengukuran diidentifikasi dari 100 konsumen OFD di Jakarta menggunakan kuesioner kemudian dianalisis menggunakan pohon keputusan. Hasil penelitian mengungkapkan terdapat lima variabel yang sangat berpengaruh terhadap belanja pembelian konsumen yaitu kesediaan membayar, frekuensi pembelian, tempat tinggal, restaurant pilihan, dan jenis restaurant. Klasifikasi pohon keputusan menunjukkan tujuh simpul dengan karakteristik konsumen yang berbeda dalam menggunakan layanan OFD. Hasil ini menunjukkan karakteristik target audiens dan klasifikasi segmentasi perilaku konsumen dalam menggunakan layanan OFD sehingga restoran dapat mempertahankan bisnis dengan melakukan inovasi yang berkelanjutan dan memanfaatkannya untuk mengetahui kebutuhan konsumen sebagai dasar pertimbangan keputusan untuk perbaikan yang lebih baik.*

Kata kunci: *Tingkah laku, transformasi bisnis, konsumen, online food delivery (ofd), pohon keputusan*

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Introduction

Indonesia has been greatly affected by the COVID-19 pandemic since March 2020. The increasing number of people affected by COVID-19 prompted the government to implement health protocols that minimized the number of activities that require people to leave their houses. In particular, many activities were forced to be held online in order to minimize the spread of the virus. In the second and third quarters of 2020, Indonesia experienced an economic recession, which disproportionately impacted the MSME sector (Medium, Small, and Micro Enterprises). Based on data from the Economic Creative Agency, 60% of culinary SMEs in Indonesia were affected by the COVID-19 pandemic.

To maintain economic stability, MSMEs had to move their businesses online by applying the principle of digitalization. In particular, the culinary MSME sector must adopt, keep up-to-date, and take advantage of the opportunities associated with app developments. BPS data show that, during the COVID-19 pandemic, the sector with the greatest proportion of online merchants was the culinary sector, which increased by 1070%. In 2020, 42% of culinary SMEs used digital platforms (IDX, 2021). MSMEs are urged to continuously innovate in order to maintain the growth of their business. Platforms serving customers that wish to purchase online food delivery services include GoFood, GrabFood, and ShopeeFood. In 2019, a survey conducted by Nielsen that reached 1000 respondents showed that GoFood and GrabFood were the most popular food delivery services, serving 58% of consumers. Similarly, ShopeeFood is one of the newest features available on the Shopee app, which was introduced in January 2021.

Restaurants must be adaptive and transform their businesses in order to continuously improve and remain competitive in response to this changing business environment. Several restaurants have had to adapt their business models to include innovative Online Food Delivery (OFD) services due to the COVID-19 pandemic (Diana et al., 2021).

This study uses behavior analysis, which classifies consumers based on the characteristics that will be identified during the analysis. Kotler (2009) states that consumer behavior is the study of how individuals, groups, and organizations select, buy and use goods, services, ideas, or experiences to satisfy their needs and wants.

The scope of this study extends to consumers in Jakarta who use OFD platforms. Surveys were distributed to consumers who used Online Food Delivery platforms via snowball sampling. This study focused on three OFD platforms: GoFood, GrabFood, and ShopeeFood. The fundamental benefit of this type of service is the streamlining of the ordering process for both the customer and the restaurant, while also saving time (Chavan et al., 2015).

Thus, based on the problem statement described above, several research questions were formulated as follows:

1. What are the characteristics of OFD platform users?
2. How can user behaviors be classified based on consumer purchase spending?
3. Based on the results of the behavior classification analysis, what are the most important attributes of an OFD platform?

This research aims to contribute to the decision-making process by providing insights that can be used by MSMEs that must constantly innovate in the face of online competition, especially in the culinary sector. Identifying patterns in consumer behavior will allow businesses to predict how similar customers or target audiences will behave in certain situations. Customer data mining is usually the center of consumer behavior models, and each model is constructed to predict the behavior of consumers in a specific situation (Chris et al., 2002). This information gained from this analysis can then be used to evaluate and conduct customer segmentation analysis as well as identify consumer needs, which consequently can help to improve the decision-making process.

The scope of this study extends to consumers in Jakarta who used the following three OFD platforms: GoFood, GrabFood, and ShopeeFood. One limitation of the study is that the analysis did not consider where the respondents lived.

Online Food Delivery

OFD is the process of preparing and delivering food to a customer that ordered said food online (Li et al., 2020). The advent of integrated OFD platforms in Indonesia, such as GoFood, GrabFood, and ShopeeFood, encouraged the expansion of OFD services. First, the consumer makes an order after selecting from a variety of restaurants via the OFD service platform's mobile application and pays for the order using one of a variety of payment methods. Following this, the restaurant receives their order and prepares the meal.

The order is then delivered to the consumer by a delivery driver. One feature that is present in all OFD applications is the ability for consumers to assess a restaurant, in which the highest rating is five stars. Customers can check the OFD apps to follow the status of their orders as well as communicate with their drivers after ordering their food. In 2019, a survey conducted by Nielsen that reached 1000 respondents showed that GoFood and GrabFood were the most popular food delivery services, serving 58% of consumers. Similarly, ShopeeFood is one of the newest features available on the Shopee app, which was introduced in January 2021. Customer demand for OFD services has increased significantly in recent years and is likely to continue to grow in the new future (Chanmi et al., 2021). Because OFD platforms allow for the contactless ordering and delivery of food, the OFD market has attracted even more attention since the COVID-19 epidemic and is expected to continue to grow its customer base (Maida, 2020).

Consumer Behavior

Consumer behavior is a key factor that affects the profitability of businesses (Rithika et al., 2021). Consumer behavior analysis helps businesses understand how customers make purchasing decisions. Understanding how consumers make choices about their product purchases may allow businesses to fill a gap in the market as well as identify acceptable and obsolete items. Consumer behavior is defined as the purchase, consumption, and disposal of items, services, time, and ideas by decision-making units (Jacoby, 2001). This behavior is widespread and affects decisions made by almost every human being in every society and culture. The decision-making process is an important aspect of consumer behavior because it provides insights into how people use their limited resources, such as time, money, and effort, on selecting, consuming, and discarding various items and services (Rithika et al., 2021).

Some researchers have categorized consumer purchasing behavior using sociodemographic characteristics (Shanshan et al., 2022; Tarek et al., 2021). The sociodemographic variables used in this study were gender, age, level of education, occupation, household composition, and region of residence. Focusing on sociodemographic characteristics and consumer traits is an acceptable starting point; however, fully explaining consumers' purchasing behavior in the online setting requires an expanded perspective (Andrea et al., 2021). Shanshan et al. (2022) assessed the effect of COVID-19 on the purchasing and consumption behavior of Chinese consumers and found that consumers buying and consumption preferences and behaviors may change due to their experiences during the COVID-19 lockdown. Tarek et al. (2021) used a variety of sociodemographic characteristics such as gender, living place, age, level of education, income, occupation, household composition, loss of employment, or salary reduction.

In the context of OFD platforms, Shalini et al. (2021) extended the classic IRT barriers in the context of the FDA by identifying three key barriers (economic, efficiency, and experience) as well as offering empirical evidence to support the negative association of barriers with trust. Li et al. (2022) examined the factors that influenced the use of the O2O delivery service; specifically, their study investigated whether the neighborhood food environment affected the consumer's choices. Diana et al. (2021) examined the impact of innovation on OFD by investigating new product services aimed at enhancing the experiential value of ordering food online using the following five variables: experiential value, willingness to order OFD, fear of COVID-19, perceived innovation, and utilitarian value.

This study directly measured the respondent's willingness to pay by using a hypothetical scenario with an open-ended question (Miller et al. 2011). The purchase frequency, number of items, and total expenditure were measured using a closed-ended question. Each of these variables has previously been determined to be an important characteristic by Pipatpong (2021), who proposed an exhaustive list of attributes that were critical to evaluating the attractiveness and competitiveness of FDAs. Mark et al. (2021) found that a consumer's purchasing behavior can be classified according to their purchase frequency, the number of items purchased per transaction, total expenditure, and willingness to pay.

In addition, this study used five variables to account for situational factors when engaging with the OFD platform: type of cuisine, type of merchant, type of order, rating, and factors influencing merchant choices. These situational factors can affect a consumer's decisions during online purchases (Andrea et al., 2022; Hand et al., 2009; Perea y Monsuw'e et al., 2004), and were measured using both closed- and open-ended questions.

The term 'situational variables' was coined by Belk (1974, 1975), who examined the influences on consumers' buying behavior in the context of 'conventional' retailers. According to Belk (1974, p. 157), situational variables refer to "all those variables specific to a time and place of observation that do not follow from knowledge of personal (intra-individual) or stimulus (choice alternative) attributes". In addition, Belk (1975) identified five types of situational elements: physical surroundings, social surroundings, temporal perspectives, task definitions, and antecedent states. According to the principles of behavioral economics, the degree to which an individual perceives certain things affects their choices and intentions both directly and indirectly (Yang et al., 2022). A consumer's buying and consumption behaviors and intentions may change due to their experiences during the COVID-19 lockdown (Shanshan et al., 2021). Therefore, the dependent variable used in this study was the consumer's choice of OFD platforms. The conceptual framework of this study is presented in Figure 1.

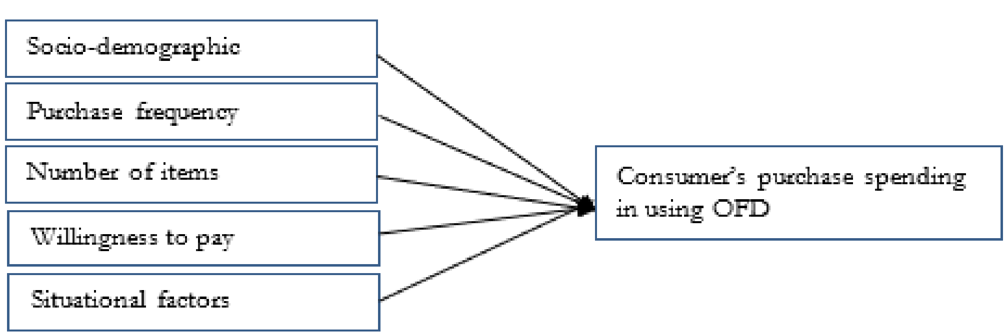


Figure 1.
Conceptual Framework Of The Study

Research Methodology

This research used a quantitative approach based on a positivist research paradigm aimed at describing a general phenomenon in more specific terms. A deductive research strategy was used in this study: an initial hypothesis was constructed based on theoretical concepts and validated using quantitative measurements; these were used as a tool to assess the theoretical concepts defined at the beginning of the study. This cross-sectional study collected all data at the same time. The data used in this research were primary data collected using a survey distributed to consumers in Jakarta who used the GoFood, GrabFood, and ShopeeFood OFD platforms.

Sampling Technique
The ideal sample size for the study was calculated using the Lemeshow test, which is primarily used for binomial outcomes. The ideal sample size for an unknown population (N) can be calculated using the following equation:

$$n = Z_{\propto}^{2}\, P(1\text{-}P)/d^{2} \quad (1)$$

where
n = the minimum sample size needed for the study
∝ = significance level
p = success proportion
d = margin of error

The Lemeshow test revealed that a minimum of 100 respondents were needed for this study. The data were collected using snowball sampling over a period of two weeks. Prior to distributing the survey, the content of the questionnaire was evaluated by distributing a pre-survey of 30 respondents. In particular, this pre-survey was used to determine the validity and reliability of this test using statistical software such as SPSS. The reliability score of the test was based on Cronbach's alpha, while the validity score was obtained using the Pearson product-moment correlation coefficient.

The questionnaire was then distributed online using Google Forms via social media such as Instagram as well as instant messaging platforms such as Whatsapp and Line. The survey was distributed in Indonesian to reach as many respondents as possible. The questionnaire used in this study contained both closed-ended and open-ended questions that were associated with the research variables. Closed-ended questions and their related categorical variables are presented in Table 1. The open-ended questions were more focused on the reasons behind choosing a specific restaurant, merchant, or OFD platform. The sociodemographic characteristics of each respondent were also collected using directed questions; these included gender, age, education, occupation, region of residence, and household composition. The 14 predictor variables and a single response variable collected using the survey are presented in Table 1.

Table 1.
Variables Involved In This Study

Variable	Category
Purchase spending (Y)	-
Gender (X1)	Male Female
Age (X2)	18-24 25-34 35-44 45 and over

Table 1. (Continued)
Variables Involved In This Study

Variable	Category
Level of Education (X3)	Secondary general education Vocational school University degree Higher degree
Occupation (X4)	In paid work (full-time or part-time) Student Home Duties Retired/pensioner None
Living place (X5)	Central Jakarta West Jakarta East Jakarta North Jakarta South Jakarta
Household composition (X6)	Single person household Living with parents Married with children Married without children Shared household
Purchase Frequency (X7)	-
Numbers of items (X8)	One item 2–3 items More than three items
Willingness to pay (X9)	Less than 20000 20000–50000 50000–100000 More than 100000
Type of cuisine (X10)	Local food Imported food
Type of merchant (X11)	Fast-food restaurant Fast casual dining restaurant Homemade Specialty store
Type of order (X12)	Heavy meal Snacks Beverage Mix
Rating choice (X13)	5 star 4.7–5 4.4–4.7 4–4.4 Less than 4
Merchant choices (X14)	Taste Rating Distance Price Others

Ethics

The survey was exclusively distributed to respondents in Jakarta. Participants were asked for their sociodemographic information on the first page of the Google Form. Google Forms is a cloud-based data management tool that is included in the Google Drive office suite that can help with the distribution of questionnaires. It can be used to design and develop web-based questionnaires and provides various options that allow for the collection of data using multiple types of questions and answers. The surveys were shared via email, instant messaging platforms, and social media. Screening questions were used to ensure that respondents were above the age of 17, used OFD platforms, and lived in Jakarta. Participants were provided with a brief summary of the study details on the first page of the Google Form and were also asked to provide their demographic information.

This page also described their right to discontinue their participation at any time. Screening questions were used to ensure that only relevant participants responded to the survey. Details of the study were explained at the start of the survey. If the recipients were interested in participating in the study, written informed consent was obtained. Respondents were reminded that the results of the survey would not be presented in a form that could potentially identify any of the respondents. Respondents were also asked to agree to have their information analyzed by requiring respondents to click the "Agree" button to confirm that they had read the information regarding their consent and permissions. Google Forms does not require users to key in respondent data manually, minimizing potential human errors during data collection. The questionnaire was distributed in Indonesian to ensure that the participants understood the details of the study and to minimize confusion.

Analysis Steps

After the research problems were formulated, the data were collected and analyzed according to the following steps:

1. Defined the predictive indicators and variables to be explored in the survey.
2. Constructed the questionnaire.
3. Conducted the pre-survey.
4. Conducted a reliability and validity test.
5. Designed the sampling methodology.
6. Conducted the survey.
7. Performed data pre-processing before dividing the data into training and testing data.
8. Analyzed the characteristics of the data.
9. Performed a regression analysis based on a decision tree algorithm. The decision tree model was developed as follows:
   a. A regression tree model was constructed by splitting nodes using the predictor variables. The model attempts to find the decision rules that maximize the degree of homogeneity in each node based on the chosen predictor variables.
   b. The trees were pruned to determine the optimal regression tree of an appropriate size.
   c. The optimal decision tree with the smallest predictive error was selected and the results of the regression tree were interpreted.
10. The optimal regression tree identified in the previous step was validated.
11. The results were analyzed.
12. The results were discussed and used to propose suggestions as well as draw conclusions about the research problems.

The workflow used in this study is presented in Figure 2.

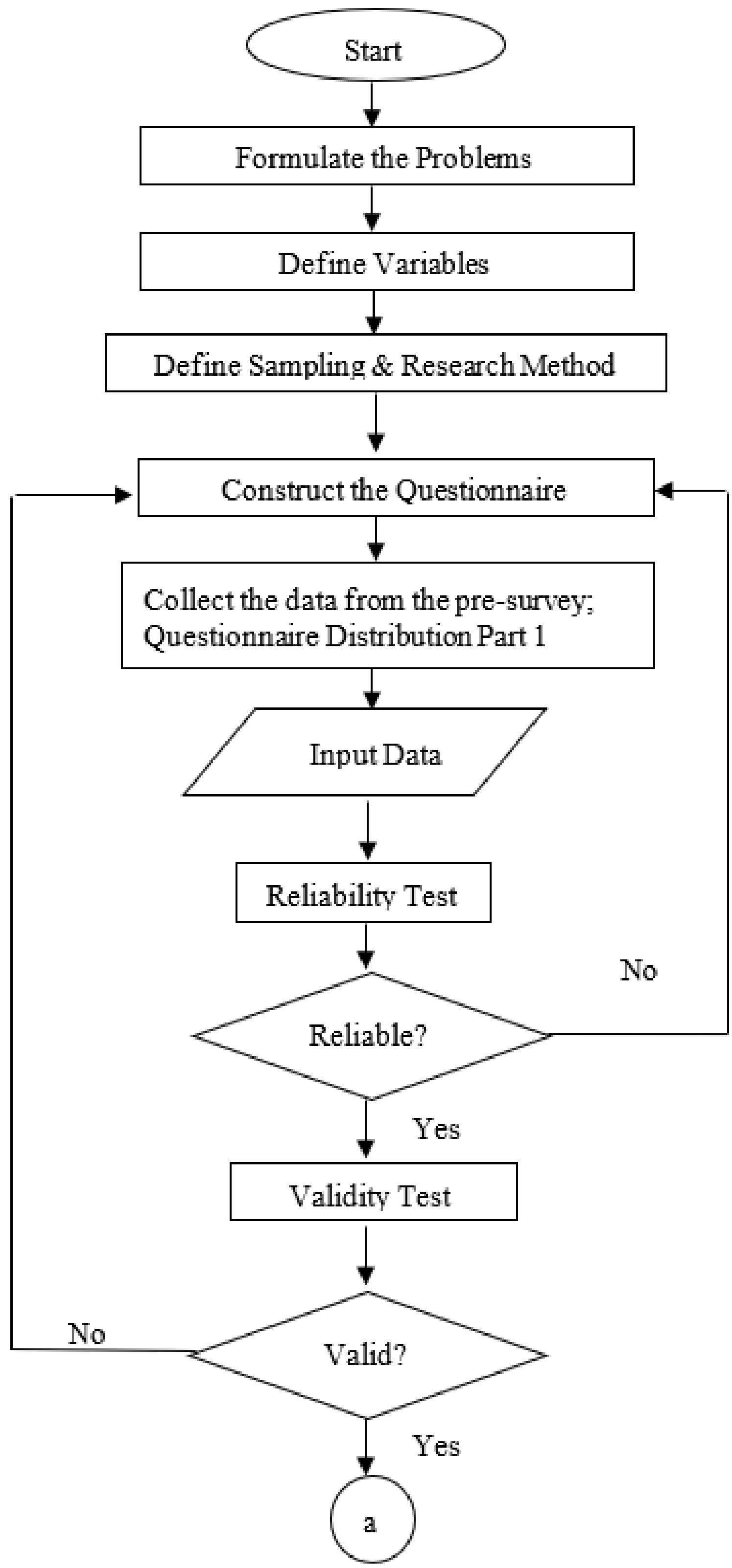


Figure 2.
Overview Of The Workflow Used In This Study.

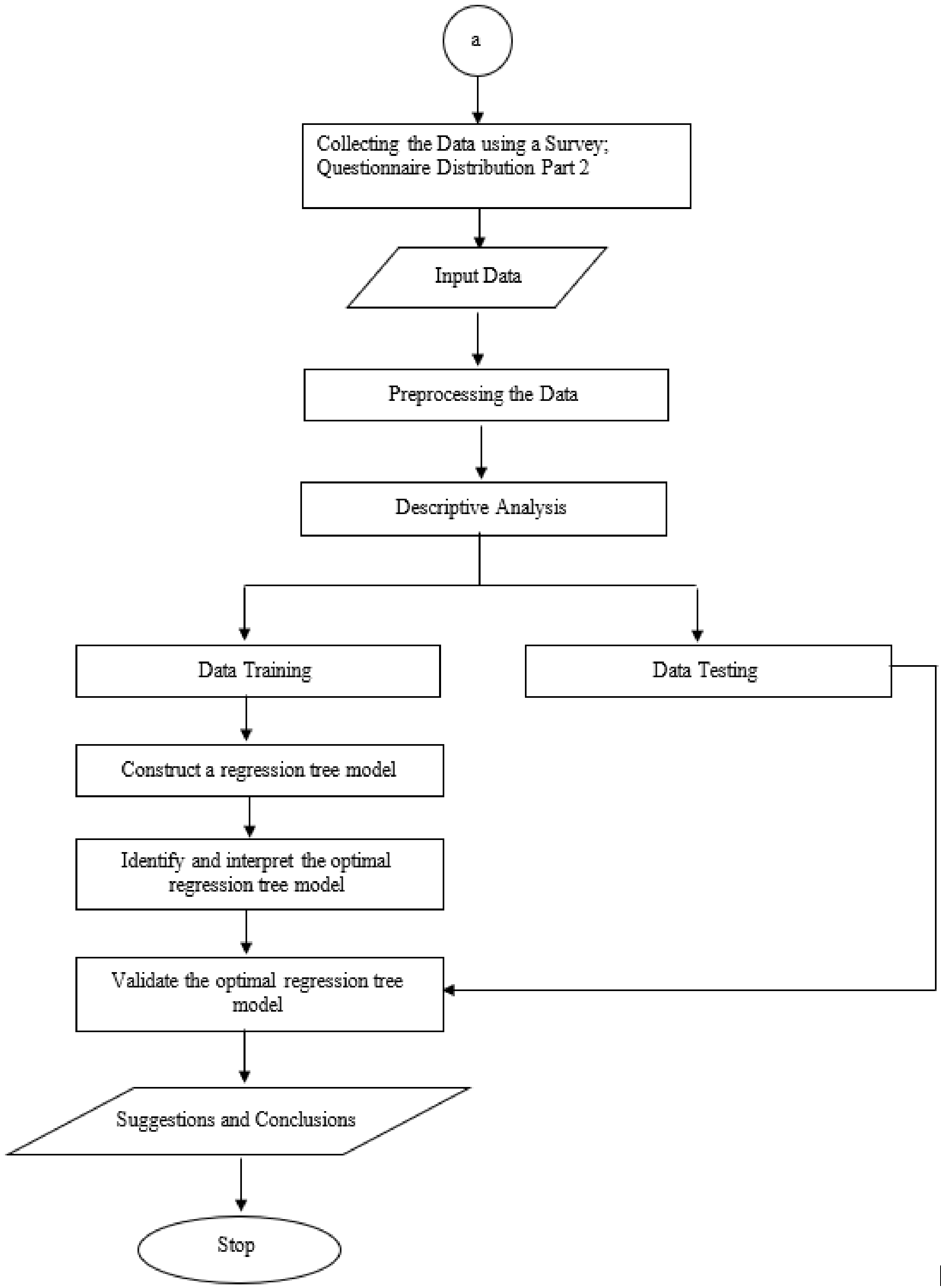


Figure 2. (Continued)
Overview Of The Workflow Used In This Study.

Results and Discussion

This section explains how the validity and reliability of the survey were assessed as well as the process of gathering, cleaning, and analyzing the data. This paper analyzed the characteristics of consumers that used OFD platforms as well as classified them in terms of their purchasing decisions on these OFD platforms using behavior analysis. Following data collection, the data must be pre-processed before analysis, including noise and missing value checks across all variables. No missing values were found in the survey results, which allowed for further analysis. The collected data were analyzed using R at a significance level of $p = 0.05$ (5%).

Results

Validity and Reliability

The validity and reliability of the questionnaire were assessed prior to its distribution. A questionnaire is said to be valid if the question/statements on the questionnaire can provide measurable information. Before conducting the main survey, validity and reliability tests were conducted on a pre-survey distributed to 30 respondents.

The validity test was conducted using a corrected item-total correlation. All variables examined in the pre-survey questionnaire had a r_{hit} greater than the R table (alpha,n-2) with an r(0,05,28) value of 0.374, which indicates that all indicators are valid. The reliability of a survey is a measure of how consistent the survey results would be if administered repeatedly (Azwar, 2000). The reliability of the questionnaire was checked using Cronbach's alpha. The value of $r_{Cronbach's\ Alpha}$ is 0.713, which is greater than 0.7. These results showed that the variables used in this research are reliable. As the questionnaire was determined to be valid and reliable, the survey was subsequently distributed to 100 respondents.

Data Analysis

Prior to classification, the demographic characteristics of the respondents were analyzed. Demographic characteristics are extremely useful for consumer segmentation as well as understanding and predicting consumer preferences in the context of OFD platforms. A total of six sociodemographic variables were collected in this study, including gender, age, household composition, education, living place, and occupation.

Table 2.
Sociodemographic Characteristics Of The Respondents According To The Results Of The Survey.

Demographic	Female	Male
Level of education		
Higher degree	3%	1%
University degree	47%	36%
Vocational degree	4%	2%
Secondary general education	3%	4%
Age		
18–24	4%	4%
25–34	50%	37%
35–44	2%	1%
45 and over	1%	1%

Table 2. (Continued)
Sociodemographic Characteristics Of The Respondents According To The Results Of The Survey.

Demographic	Female	Male
Occupation		
Full-time or part-time work	50%	38%
Home Duties	2%	1%
Student	5%	4%
Household composition		
Single person household	20%	21%
Living with parents	21%	13%
Married with children	7%	4%
Married without children	6%	3%
Shared household	3%	2%
Living place		
Central Jakarta	21%	14%
West Jakarta	11%	9%
East Jakarta	7%	4%
North Jakarta	2%	3%
South Jakarta	16%	13%

The sociodemographic characteristics of OFD users in Jakarta, except for gender, are presented in Table 2. Demographic information can be used to understand consumer behavior in the context of OFD platform usage.

Figure 3 illustrates the main reasons why consumers chose a particular merchant/restaurant and shows that the dominant reason a consumer chose a specific merchant/restaurant when ordering on OFD platforms was the price of the meal (38% of respondents).

This was consistent with respondents' choice of OFD platforms: consumers preferred the platform that offered the most discounts, vouchers, and promotions, which consequently reduced the price of the food/beverages available on that platform compared to its competitors. The least important factor was the "Others" category (3% of respondents).

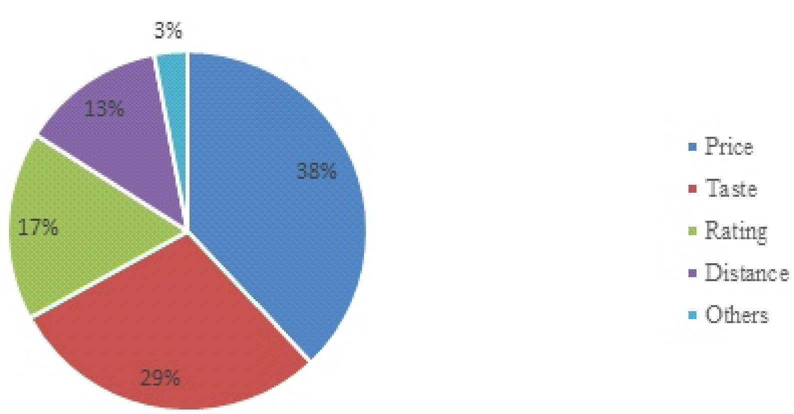
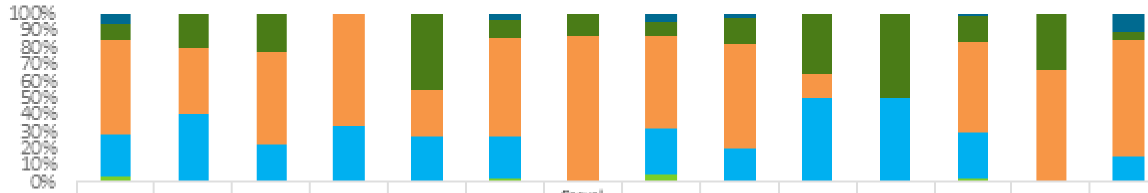


Figure 3.
The Factors That Influenced A Respondent Choice Of Merchant Or Restaurant.



	Type order				Type cuisine		Type merchant				Rating choice			
	Heavy meal	Beverage	Mix	Snacks	Imported food	Local food	Casual dining restaurant	Home made style	Restaurant fast food	Speciality store	4.4 - 4.7 star	4.7 - 5 star	4 - 4 star	5 star
> 100000	3%	0%	0%	0%	0%	3%	0%	2%	1%	0%	0%	1%	0%	2%
50000-100000	5%	1%	9%	0%	5%	10%	1%	3%	6%	5%	2%	11%	1%	1%
30000-50000	30%	2%	21%	2%	3%	52%	7%	21%	25%	2%	0%	40%	2%	13%
15000-30000	13%	2%	9%	1%	3%	22%	0%	10%	8%	7%	2%	20%	0%	3%
< 15000	2%	0%	0%	0%	0%	2%	0%	2%	0%	0%	0%	2%	0%	0%

OFD attribute based on consumer's purchase spending

Figure 4.
The Distribution Of Consumer Spending Based On OFD Attributes.

Their main reason for choosing a specific merchant/restaurant was their favorite choice.

Figure 4 shows the distribution of consumer spending based on OFD attributes. The data show that the attribute with the strongest influence on consumers with an average amount of spending was the type of order: 30% of consumers who spent "30,000–50,000" in a single transaction ordered a heavy meal, while 21% ordered a mixed meal. In addition, OFD users in Jakarta were overwhelmingly more likely to choose to purchase local food rather than imported food at levels of expenditure. Consumers generally chose fast-food restaurants (40% of all respondents at all spending levels) over casual dining, homemade, and specialty stores. In particular, 25% of all respondents who used OFD platforms purchased meals from fast-food restaurants at a spending level of 30,000–50,000. In terms of the rating of the restaurant, most consumers chose OFD services with a rating of 4.7–5 stars (74% of respondents), with the dominant category being those who spend 30,000-50,000 per transaction.

Decision Tree
Before constructing the decision tree model, the data was first separated into training and testing data in a 7:3 split. The regression tree model uses the independent variables collected from the survey to inform the decision rules used and the characteristics of the nodes formed using the model. The most important independent variable will be used as the first node in the model, and the data will be continually classified until the terminal node is reached. Optimizing the model takes place over three stages: tree formation, tree pruning, and optimal tree selection. The process of making a decision tree model using the 14 predictor variables and 1 response variable identified in the survey is explained in the following sections.

Regression tree formation
The formation of the regression tree model begins by sorting the behavioral data of OFD users, which is reflected in the 14 predictor variables. Since each predictor variable can be sorted by different amounts, there can be as many as n-1 ways of sorting the independent variable. In this study, eight independent variables with a varying number of nodes were used to disaggregate the data.

After finding all possible ways of disaggregating the independent variable using each of the predictor variables, it is possible to select the best decision rule for each predictor variable using a variety of metrics, including the goodness of split criteria. The best decision rule is one that maximizes the degree of homogeneity within each node relative to the size of the parent node and the size of the split between the two child nodes. The most important node is node 1: this represents the most influential variable. Following this, each decision rule will produce two data groups called the right child node and the left child node, which are labeled node 2 and node 3, respectively. The classification continues until there is no significant decrease in heterogeneity at the child nodes. In this study, the maximum depth of the regression tree was set to 15 nodes. Nodes that can no longer be sorted are known as terminal nodes. As the tree grows, each node will be divided into two groups that are more homogeneous than the previous node.

The Tree Pruning Process

A regression tree with a large depth can result in errors due to complexity. Thus, the regression tree was pruned to obtain a simpler regression tree model (i.e., a model with a shallower depth) without compromising on its predictive power. The pruning process is conducted until an optimal tree with a minimum cost complexity was produced. The optimal regression tree model was found to have 7 nodes compared to the original maximum depth of 15 nodes.

Optimal Tree Selection

The optimal regression tree obtained contained seven terminal nodes. In the optimal regression tree model, it was found that not all predictor variables affected consumer spending. In this process, it tends to be chosen to estimate the response variable. 10% of all respondents were classified into the first terminal node, while the second terminal node accounted for 20% of all respondents. Terminal nodes 3–7 accounted for 11.4%, 10%, 12.8%, 11.4%, and 24.3% of all respondents, respectively.

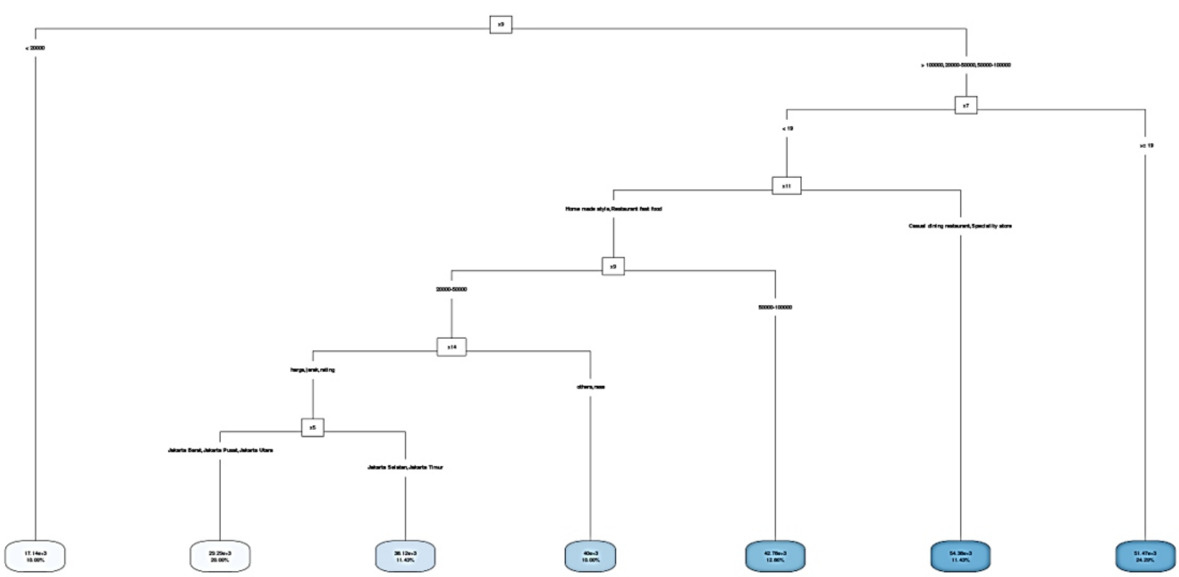


Figure 5.
The Optimal Decision Tree Obtained From The Data.

The optimal regression tree is presented in Figure 5. Of the 14 predictor variables collected in the survey, only five were included in the optimal regression tree model: willingness to pay, purchase frequency, type of merchant, merchant choice, and region of residence. The first decision rule was based on the consumer's willingness to pay in terms of the amount of money spent per transaction when using OFD services; respondents who spent less than 20,000 in a single transaction were separated from those who were willing to spend "20,000-50,000", "50,000-100,000", and ">100,000". The latter node was then sorted by monthly purchase frequencies into "< 19" and ">= 19" categories. The third node sorted consumers who had purchased from OFD platforms at a monthly frequency of < 19 based on the type of merchant they preferred, with two categories: "homemade style and fast-food restaurants" and "casual dining and specialty stores". The former category was then sorted into consumers who were willing to spend "20,000–50,000" and "50,000–100,000" per transaction.

The next decision was focused on the reasons why a consumer selected a specific merchant, separating respondents who were focused on "price, distance, and rating" from consumers who were focused on "taste and the 'others' category". Finally, the node containing the consumers who were interested in "price, distance, and rating" was split according to the respondent's region of residence, with the following two categories: "Central Jakarta, West Jakarta, and North Jakarta" and "East Jakarta and South Jakarta". Table 3 presents the importance scores of the variables used in the optimal regression tree. Table 3 shows that the most important variable was the consumer's willingness to pay, which had an importance score of 42, while the second and third most important variables were the type of merchant and purchase frequency, which had importance scores of 18 and 16, respectively. Variables that did not influence consumer spending on OFD platforms included gender, type of order, and choice of rating, each of which had an importance score of 0.

Table 3.
Importance Scores of Variables used in the Optimal Regression Tree.

Variable	Score
Willingness to pay (X9)	42
Type of merchant (X11)	18
Purchase frequency (X7)	16
Age (X2)	6
Level of education (X3)	6
Living place (X5)	4
Occupation (X4)	3
Merchant choice (X14)	2
Household composition (X6)	2
Type of cuisine (X10)	1
Number of items (X8)	1
Gender (X1)	0
Type order (X12)	0
Rating choice (X13)	0

Table 4.
Characteristics Of The Terminal Nodes Formed By The Optimal Regression Tree Model.

Node	N	Description
1	7	OFD consumers who were willing to pay <20,000 per transaction. Respondents in this node had an average expenditure per transaction of 17,000.
2	14	OFD consumers who were willing to pay 20,000-50,000 per transaction, had an average monthly purchase frequency of <19, preferred homemade style food or fast-food restaurants, chose their favorite restaurants based on price, rating, and distance, and lived in West Jakarta, Central Jakarta, or North Jakarta. Respondents in this node had an average expenditure per transaction of 29,000.
3	8	OFD consumers who were willing to pay 20,000-50,000 per transaction, had an average monthly purchase frequency of <19, preferred homemade style food or fast-food restaurants, chose their favorite restaurants based on price, rating, and distance, and lived in South Jakarta and East Jakarta. Respondents in this node had an average expenditure per transaction of 38,000.
4	7	OFD consumers who were willing to pay 20,000-50,000 per transaction, had an average monthly purchase frequency of <19, preferred homemade style food or fast-food restaurants, and chose their favorite restaurants based on taste or other factors. Respondents in this node had an average expenditure per transaction of 40,000.
5	9	OFD consumers who were willing to pay 50,000-100,000 per transaction, had an average monthly purchase frequency of <19, and preferred homemade style food or fast-food restaurants. Respondents in this node had an average expenditure per transaction of 43,000.
6	8	OFD consumers who were willing to pay >100,000 per transaction, had an average monthly purchase frequency of <19, and preferred casual dining and specialty stores. Respondents in this node had an average expenditure per transaction of 54,000.
7	17	OFD consumers who were willing to pay >100,000 per transaction and had an average monthly purchase frequency of ≥19. Respondents in this node had an average expenditure per transaction of 54,000.

In the optimal regression tree model, the consumer's willingness to pay (X9) was the most important variable and was used to separate OFD users in Jakarta into two groups, with 7 OFD consumers separated into a node based due to having an average spending of <20000 in a single transaction. The other node contained 63 OFD users who had an average spending of "20,000–50,000", "50,000–100,000", or ">100,000" per transaction.

The purchase frequency (X7) variable was then used to divide OFD consumers in Jakarta into two groups: 46 consumers who had an average monthly purchase frequency of "<19" and 17 consumers who had an average monthly purchase frequency of "≥19". The type of merchant (X11) variable was then used to divide the former category into two groups: 38 OFD consumers who chose to purchase from merchants selling homemade food or fast food, and 8 OFD consumers who chose to purchase from casual dining and specialty stores.

The former category was then divided by their willingness to pay (X9), with 29 OFD consumers who spent "20,000–50,000" in a single transaction, and 9 OFD consumers who spent "50,000–100,000". The former category was once again divided by their choice of merchant (X14) into two groups: 22 OFD consumers who chose restaurants based on "price, rating, and distance" and 7 OFD consumers who chose restaurants based on taste and other variables. Finally, the last node was split according to their region of residence (X5): 14 OFD consumers who lived in Central Jakarta, North Jakarta, or West Jakarta, and 8 OFD consumers who lived in East Jakarta or South Jakarta. The characteristics of each of the seven terminal nodes obtained are presented in Table 4.

Table 4 shows that the OFD users with the highest average spending per transaction were from the group that were willing to pay more than 100,000 per transaction and had a monthly purchase frequency of more than 19. These characteristics suggest that a consumer's condition and/or situation can change their preferences and behaviors, especially in terms of using OFD services on a daily basis. In the present day, as the market share of OFD services has expanded, researchers have paid more attention to OFD consumers and how they make decisions (Chanmi et al., 2021). It is thus important for businesses to innovate, as it can is clear that the increased frequency of OFD use during the COVID-19 pandemic has already changed the habits of many of the respondents in this study. This changing behavior represents an opportunity for innovations and the transformation of businesses from online to offline. Any business innovations must respond to the growing demand for OFD services (Diana et al., 2021).

Validation of the optimal regression tree model

RMSEp (Root Mean Square Error of Prediction) is a metric that can be used to determine the optimal regression tree model. A good regression tree model can make predictions from new data or observations.

The data used in the model development process is known as the training data, while the data used to validate the model is known as the testing data. In this study, the testing data is comprised of 30 respondents and was used to validate the optimal regression model obtained. This will validate the model's ability to predict the purchasing behavior of OFD (GrabFood, GoFood, and ShopeeFood) consumers in Jakarta.

Table 5.

$Rmse_p$ of The Optimal Regression Tree Model.

Metric	Value based on Testing Data
$RMSE_p$	0.495

Table 5 presents the results of the validation test, which shows that the model has an $RMSE_p$ of 0.495. A lower $RMSE_p$ value is indicative of a better model.

Discussion

The main purpose of this study was to investigate the factors that influence the amount of money that a consumer spends on OFD services. The importance score results show that the primary influence on customer spending was the consumer's willingness to pay. Surprisingly, 68% of respondents were willing to buy food and beverages at higher prices using OFD platforms during the COVID-19 pandemic compared to using offline stores. Almost all respondents thought that the COVID-19 pandemic changed their purchasing habits. This was consistent with the tremendous increase in demand for OFD services, which is expected to continue to grow in the near future (Chanmi et al., 2021). The average OFD consumer was willing to pay between 20,000–50,000 per transaction (73% of respondents). Thus, the proposed conceptual model was validated by the empirical analysis of data collected in Jakarta, Indonesia.

According to the optimal decision tree model obtained, the five OFD characteristics that most strongly affected a consumer's spending were: willingness to pay, purchase frequency, type of merchant, factors that affected their choice of merchant, and region of residence. The optimal decision tree model also showed that gender, type of order, and the rating of the restaurant did not affect consumer spending.

An analysis of sociodemographic characteristics of OFD consumers shows that most consumers had a University degree, were between 25–34 years old, and engaged in either full-time or part-time work. In addition, 41% of consumers were from single-person households. A majority of OFD consumers lived in Central Jakarta compared to the other municipalities. Some studies have shown that sociodemographic characteristics can influence a consumer's likelihood of purchasing food online (Saphores and Xu, 2020; Wang and Somogyi, 2019). This study was consistent with the literature except for gender, which was found to have an importance score of zero during optimal tree selection.

In terms of situational factors, which included the type of cuisine, type of merchant, type of order, choice of restaurant rating, and choice of merchant, only the rating choice and type of order had zero influence on tree selection. This suggests that these variables do not affect consumer spending on OFD platforms. Previous studies have shown that online ratings can be used to promote a merchant's reputation, which can affect consumer purchases (Jabr and Zheng, 2014) and the market share of the business (Chevalier and Mayzlin, 2006). Thus, it is crucial to pay attention to ratings from online reviewers, as higher online ratings will lead to a more favorable view of the restaurant (Lingfei et al., 2022). However, this study showed that a restaurant's rating did not influence a consumer's spending because of the number of attributes that included in this selection were many so that this can be occurred especially in the pruning tree selection process.

The most important situational factor that influenced OFD consumer spending was a consumer's willingness to pay, with consumers who were willing to spend 30,000–50,000 in a single transaction making up more than 50% of respondents. In addition, more than 50% of respondents purchased heavy meals, while almost 75% of respondents bought local food. 40% of respondents chose to patronize fast-food restaurants. More than 70% of respondents chose merchants who had ratings between 4.7–5 stars. 61% of respondents bought an average of 2–3 items per transaction. The purchase frequency data showed that 70% of respondents used OFD services less than 15 times per month.

In this study, OFD consumer spending was classified using a decision tree. The optimal regression tree model obtained revealed that consumer behavior was best represented using seven terminal nodes (Table 4). The analysis also showed that almost all factors identified in this study were important to classify consumer behavior, except for gender, choice of rating, and type of order. However, only five attributes were used in the optimal decision tree: willingness to pay, purchase frequency, type of merchant, choice of merchant, and region of residence. These results show that these factors had a greater effect on OFD consumer spending compared to the other attributes. Each of these nodes represents a segment of OFD platform users in Jakarta based on their purchasing behavior.

Implications

This study reveals several unique insights that can have practical implications for OFD stakeholders. Based on the behavior analysis of OFD consumer spending, OFD marketers or merchants can consider the average consumer's needs as well as direct OFD consumer choices based on their average spend per transaction. Although only five attributes were used to generate the seven terminal nodes that represent customer purchasing behaviors, almost all of the attributes used in this study were found to be important during the optimal tree selection process.

Furthermore, OFD services can be beneficial during a pandemic such as COVID-19 since they reduce customer-restaurant interaction and allow customers to eat meals from their favorite restaurant at home, allowing restaurants can maintain their business models while constantly innovating using the segmentation information obtained from this study. This data can be used to understand consumer needs, which can lead to improved decision-making. Second, and perhaps most crucially, as the market share of OFDs continues to expand, researchers have paid more attention to OFD consumers and how they make decisions (Chanmi et al., 2021); thus, the results of this study can provide insights into OFD consumer decision-making that stakeholders can use to leverage and innovate their business models in the future, especially since the demand for OFD services has greatly increased due to a change in the habits of respondents as a result of the COVID-19 pandemic. These changing preferences must be the focus of restaurants/merchants who are aiming to adapt and survive in a competitive market.

Furthermore, restaurants should be aware and understand how their characteristics and participation in OFD platforms can affect their operational procedures and customer satisfaction. Third, a consumer's willingness to pay was found to be the most important factor that influenced an OFD consumer's spending. This shows that as long as the restaurant/merchant fulfills consumers' needs and can cater to a consumer's preferences, then consumers are willing to pay for food/beverage despite increased prices. This is supported by the finding that more than 70% of OFD consumers were willing to pay higher prices on OFD platforms rather than eat offline during COVID-19. This changing behavior can be an opportunity for marketers to innovate and transition from an offline business to an online business. Any innovations must respond to the growing demand for OFD services (Diana et al., 2021).

Finally, the OFD consumers in this study were almost exclusively from Generation Y and Z during COVID-19; thus, OFD stakeholders should focus on discounts, vouchers, and promotions to optimize business growth. It is important to remember that this study found that consumers used the OFD platforms that offered the most discounts, vouchers, and promotions, which can reduce the price of food and beverages compared to other platforms. Since the younger generation utilizes SNSs to communicate with each other, OFD service marketers should also use these services to run competitions and/or provide discount codes (Williams and Page, 2011). Information can also be distributed using social media platforms, such as Instagram and Twitter. Furthermore, promoting OFD services through social media can appeal to younger generations.

Limitations and Future Research

As with any research, this study had several limitations. This is the first study that attempted to classify the behavior of OFD users and was intended to fill the gaps in the literature. This thus sets a baseline for future studies on the impact of the pandemic in terms of the behavior of OFD users. The surveys were distributed in Jakarta, Indonesia. As the effects of the COVID-19 pandemic are likely to vary between each country, not only in terms of epidemiology but also, among other things, the baseline situation and shock resilience of the nation (HLPE, 2020). Thus, the results of this study cannot always be generalized to other countries. Furthermore, this study faces some sample size issues, especially since only 100 responses were collected due to time limitations, which may limit the representativeness of the dataset in terms of OFD consumers in Jakarta. Consequently, this limits the generalizability of these findings to the entire population of Jakarta. Future work should extend the framework of this study by examining additional variables or attributes that can influence OFD consumer behavior in terms of consumer spending.

In addition, because this study only focused on one machine learning technique for the classification process, future research should investigate the use of other techniques and compare the classification results. These additional investigations would expand researchers' understanding of the results based on the different techniques used, thereby allowing for a more meaningful assessment of the potential barriers to better predictions of OFD consumer behavior.

Conclusion

This paper highlights the importance of understanding the segmentation and characteristics of OFD consumer behavior based on consumer spending as well as the importance of exploiting the possibilities and opportunities offered by rapid innovation and business transformations during the COVID-19 pandemic. This is especially the case for restaurants, merchants, and OFD stakeholders, who should update and innovate their operations to cater to the changing needs, behaviors, and consumer preferences during COVID-19. These actions will have crucial consequences in the future. In addition, these changes will be crucial in helping restaurants/merchants adapt and survive in a competitive market. Furthermore, this study also provides new information and insights for all OFD stakeholders, allowing marketers at MSMEs restaurants (SMEs) and OFD platforms (e.g., GrabFood, GoFood, and ShopeeFood) to be more aware of the characteristics of OFD users and factors that affect customer satisfaction, allowing them to make more strategic marketing decisions in terms of their operational procedures.

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