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Research Article

Ride-Hailing Landscape in Indonesia: A Segmentation Analysis Perspective

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Abstract: *The objective of this paper is to find factors that affect the decision-making of ride-hailing users that focus on the transportation perspective, and assess each importance of factors on each segmentation. This paper uses a mixed method approach with the objective of in-depth interviews to find important factors in the decision-making of using ride-hailing services for transportation. Then, Factor Analysis is conducted to confirm whether the factor fits the analysis. Lastly, CA or Cluster Analysis is performed to segment the users of ride-hailing transportation. The outcomes of this study found that there are four segments in this study, one segment was found to be not a price-sensitive group, while the other are price sensitive. In general, factors of empathy were found to be influential in decision-making and reducing the price-sensitive thoughts of users. However, each segment has its own uniqueness of importance factors. The study is only focused on the industry, not on specific companies; thus, the implication will be general. Although most segments are price sensitive, if the company can identify important factors for them, there are indications that they will be less price sensitive. Segmentation one and four are the most suitable ones to be targeted by the marketer. It is known that both segments are prioritizing competence and empathy factors when choosing ride-hailing applications. These factors can be evaluated through past experience.*

Keywords: *Cluster analysis, Customer segmentation, Factor analysis, Price sensitive, Ride hailing industry, Service quality.*

I. INTRODUCTION

Mobility has become a crucial part of the digital era, as it plays a significant role in addressing the challenges of urban population growth (Barreto et al.,2020); one of the most popular alternatives to increase mobility is ride-hailing service. Ride-hailing has contributed to improving city mobility efficiently since it serves millions of passengers in big metropolitan cities in Indonesia (Auditya et al., 2022). Based on Spire research (2023), the estimation of the market size of ride-hailing in Indonesia is US$10.6 million, this is an indication that Indonesian ride-hailing is in its growth stage.

By definition, ride-hailing is digital services that connect partnered-drivers and passengers in real time, providing door-to-door connectivity for passengers (Kumar, 2022). Ride-hailing services offer their customers wide options in mobility services, from flexible options of destination to the preference of transportation. In common two common options of transportation are usually used in ride-hailing services, including 2 wheels and 4 wheels, and each provider also has various additional options that are influenced by pricing, waiting time, and traveling distance (Ashkrof, 2021).

Indonesia has made progress on its digital transformation; it can be projected on the growth of Indonesian internet users. More and more people in Indonesia have been connecting to the internet during the past five years. About 143.26 million people in the country used the internet in 2017, and by 2022, that number had risen to a staggering 224.01 million. It is anticipated that by 2028, Indonesia will have an even higher number of 282.5 million internet users. This shows that the digital economy in Indonesia is one of the promising sectors in the future (Nurhayati, 2023).

Assessing the ride-hailing market, currently, Indonesia has four key players, including InDrive, Maxim, Grab, and Go Jek. Furthermore, the key players are eager to win the hearts of customers by providing numerous services for the customers. Thus, the competition from the ride hailing industry becomes highly competitive. The assumption of competitiveness comes from the similarity of offerings from both companies and fluctuations in market share from both companies. That is why conducting promotions through customer incentives/discounts is heavily done in an effort to attract both current and new customers. However, the effort of promotion through giving a customer incentive (discount) is not too effective. The market share between Go Jek and Grab fluctuated and depended on the share of customer incentives (Sheng & Charlie, 2022).

Due to the low switching cost and vast network (multi-homing), users can participate in more than one platform (Smichowski, 2018). This occurs in ride-hailing companies, where the companies' users can easily change their alternative to ride-hailing services due to similarities in features and experience (Khuntari, 2022) and the simplicity of exiting the market. In extent, users can use both services without any monetary switching cost (Smichowski, 2018); if they do not find anything interesting or cheaper, they just exit the app and change to other alternatives, as simple as that. Researchers did preliminary research on 72 users of ride-hailing, and it is proved that most users depended on lower prices or higher price discounts in choosing ride-hailing transportation services (Exhibit 1.). It was found that 75% have a tendency to choose a service based on a lower price and switch their preference if the other applications have a lower price.

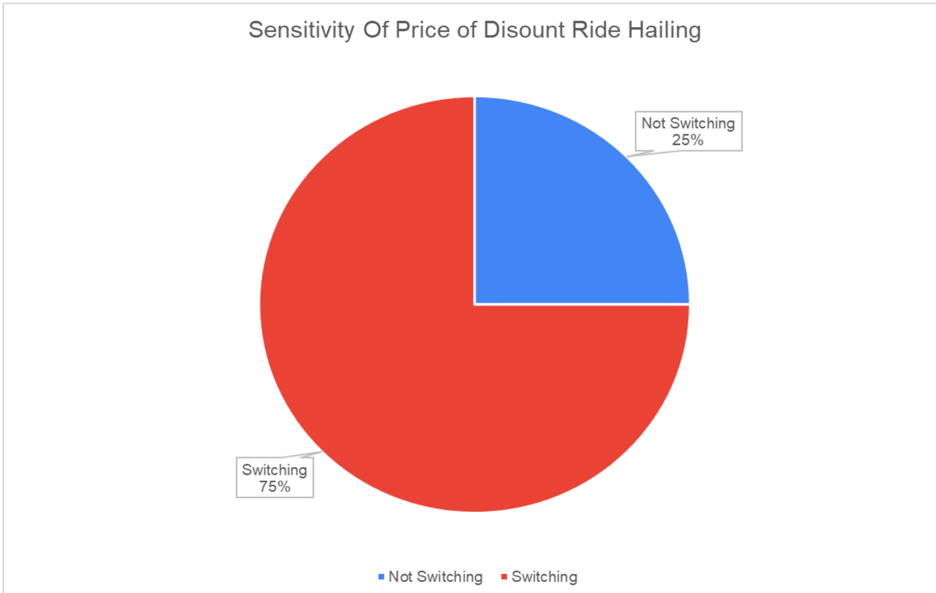

Fig. 1 Sensitivity to Discount N=72 Users

Segmentation of ride-hailing users is necessary for several reasons. First is due to the low switching cost where users can participate in different applications, and even they can switch between different ride-hailing services based on their preferences. This creates an urge for ride-hailing companies to understand the specific needs and preferences of different users in order to tailor an effective offering. Additionally, it is shown that users often choose ride-hailing services based on price; therefore, segmentation can identify a non-price-sensitive and customized service effectively for price-sensitive segments. Lastly, segmentation can also help companies identify niche markets or underserved segments that use specific features.

II. LITERATURE REVIEW

A) Market Segmentation

Market segmentation, by definition, is a group of customers who have a similar set of needs, dividing a large number of markets into a smaller one (Saayman, 2019; Kotler & Keller, 2021). Based on Kottler & Keller (2021), market segmentation is commonly distinguished into four categories: including demographic, geographic, behavioral, and psychographic. Demographic segmentation consists of several variables related to the structure of the population, such as age, family size, life cycle, gender, income, occupation, and other social class classifications. The reason why demographics are one of the considerations in segmentation is that, usually, different demographics of people may result in different attitudes and behavior.

Geographic segmentation distinguishes the market into geographic units that are related to the nations, states, regions, cities, and counties. The reason is that the company might have operated its business in a specific area; by using the geographic data combined with the behavior, the company could get the data related to the needs of local people. Behavioral segmentation categorizes a group based on their actions, which can be tracked from the usage rate of the product, loyalty status, buyer-readiness stage, user status, and occasions. In detail, user status is a classification of consumers, which commonly can be classified into non-users, potential, regular, and ex-users. By this, the company could seek each customer experience based on classification that later on tailored into different approaches to marketing strategies. On the other hand, by means of buyer-readiness stage could help the company identify at which stage the customers are into the product, are they already know about the product, and whether they are interested in the product or not. Psychographic segmentation is dividing a group of people based on their psychological traits, lifestyle, or values.

This approach of segmentation is important since demographic, geographic, and behavioral characteristics do not always precisely reflect their underlying needs in purchasing a product. Consumers might have motivation guided by knowledge and principles, which will affect their decision to buy a product. In the current digital era, customer segmentation has become broader and more complex. In addition, with the interconnected system, digital platforms can grab a wide scope of customers through the application. Thus, the company needs to have an integrated system of data from the customer so that they can be more intimate through personalized services and information for communication and offering (Russkaia & Eremenko, 2019). With the development of machine learning, the marketer can use it as a tool to identify the customer. Hence, they know more about them, so the marketer can make a more accurate approach and offering. Research from (Ullah Et al., 2023) has already implemented such an algorithm in identifying valuable and loyal customers, which leads to an effective marketing strategy. In detail, the implementation of machine learning in identifying customer segmentation, can also help companies in offering a premium price to the precise user who has higher willingness. That personalized pricing policy helps both the marketing and financial manager in increasing their margin without damaging their customers (Zhao, 2021).

B) Price Sensitivity

A certain response to changes in prices for products or services of an individual refers to price sensitivity (Monroe, 1973). The response to a change in price is quite natural since, by definition, price is an action of sacrifice or giving up (in monetary terms) to obtain a product (Zeithaml, 1988). Indifferent products in a specific market may result in higher price sensitivity from consumers. By that means, companies have similar offerings to the customers, so their products or services are perceived to be similar. Thus, from the perspective of consumers, to get the best value for a product, they would likely prefer a lower price in the market; that is why the price sensitivity from consumers can be identified from the similarity of a product (Kottler & Keller, 2021). With the diversity of market segmentation, the price sensitivity of a certain product could also be different from one group to another (Kolhede et al., 2022). Thus, it is essential to identify the price expectations of a segment so that the company can make better offerings to the target segment (Kottler & Keller, 2021).

The different price sensitivity of a certain product in different groups, shows the essential of segmenting or classifying the group of population in a market. A related study of price sensitivity in different demographic segments shows different responses to changes in the prices of a product or services (Kolhede et al., 2022). In implication of that, the company should identify the segment which is less sensitive in the market, and maintain the insensitivity of price changes. Additionally, the segments which are less sensitive to the price are more controllable through the marketing effort (Yun & Hanson, 2020). To an extent, ride-hailing providers in Indonesia have shown a similar offering in the market; thus, the survey conducted in the issue statement implies that the market of ride-hailing has high price sensitivity. A similar study from Phouc et al. (2021) supports the study in price sensitivity of the ride hailing market. The price sensitivity of an individual affects their attitude toward using ride-hailing services. Thus, it resulted in their intention to use the ride-hailing services. By this means, the customer is proven to take a consideration price while choosing the ride-hailing services; thus, the sensitivity level of price in ride-hailing is applied.

C) Service Quality and E-Service Quality

Service quality is stated to be one of the important factors which affect the satisfaction of customers (M.Dimaro, 2023). Furthermore, fulfillment of service quality reflected an accomplishment of the company in alleviating customer problems by meeting their expectations (Udayalakshmi & Sridevi, 2023). Thus, service quality, in this case, can have a consequence effect on the post-purchase behavior of customers and decision-making of choosing their preference of service in the future. In the ride-hailing context, since the service dimension of this sector combines between offline and online aspects, the evaluation of service quality is based on those two aspects.

Thaithakul et al. (2021) proposed an evaluation dimension of service quality for ride-hailing in Bangkok, the dimension includes two major aspects, which are offline service quality and online service quality. In offline service quality it branches into three aspects, which are competence, empathy, and information congruity. Both of these two aspects, namely competence and empathy are reflected and given by drivers, which act as the medium of the company for delivering its services. At the same time, information congruity is the congruence of offering to the real service delivery. The competence dimension reflects the skills and job accomplishment of the driver fulfilling the service delivery. Empathy, in this case, reflects the act of service and the ability of the driver to know the emotions of customers and act based on their interests.

On the other hand, online service quality evaluation has two dimensions, which include structural assurance and platform responsiveness. The aspect of structural assurance shows the safety side of the application, which can deliver enough safeguards for the users which make them feel comfortable in using the ride-hailing platform; this includes the safe transaction and legal structures of the application. At the same time, platform responsiveness is the responsibility of the application in responding to the demand from the customer.

D) Bargaining Power of Customers

Porter (1980) introduced a tool to analyze the competitiveness of the market, which is called Porter 5 Forces. However, the discussion in this paper is limited to only the customer side. One of the factors is the bargaining power of customers; by that means, the customers have the power to make pressure, which will affect the lower price, increase quality, and better customer service of a product. In detail, a high power of bargaining of customers leads to the inability of the company to increase the margin; consequently the company which has high bargaining power of customers would likely experience a lower profitability (Chang et al., 2021). Thus, in that particular market, the company has pressure from the customer, if they increase the price of the product, there is a chance that the customers will exit from the market and change to an alternative or similar product. One of the reasons why the market has high customer bargaining power is because of the low switching cost (Mawdsley, 2022). The reason is that the comparison of the company's product to the competitor is similar; thus, they have a similar offer, and a similar offering means that they offer a similar value proposition to the customer, and consequently, it leads to low switching cost (Dong, 2020).

E) Specific Attributes in Each Segmentation

The importance of attributes in the decision-making process gives an urgency for the company to know how to identify what are the most important attributes from the perspective of consumers. The expectation generated by the customer resulted in several key attributes related to the product or service quality (Kottler & Keller, 2021). However, not all populations have the same attributes toward their decision to buy some products and services. Studies related to service quality found that different segmentations resulted in different quality perceptions (Aksu et al., 2020). In addition, different segmentations also resulted in different importance of attributes; even in several segmentations, price is less important (O'Neill et al., 2022). Knowing the market segmentation in identifying the importance of attributes generated by each group's perspective has been a practice for a decade (Aksu et al., 2020; O'Neill et al., 2022; Rosal et al., 2023). Thus, the company should identify the expectations of customers toward its product so that, in the end, if the product meets the customers' expectations, it will result in customer satisfaction. (Kardiyasa, 2023; Suchanek, 2023).

F) Previous Studies of Preferences in Ride Hailing Market

While this paper still presumably assumes that price is one of the main factors of customer decision-making in ride-hailing, reflected on the price sensitivity survey (Exhibit. 3) and previous findings (Phouc et al., 2021), it still needs to be analyzed more, on other factors, since different segment has their own main factors that take into account on decision-making process (Kottler & Keller, 2021), even different groups have different price sensitivity (Kolhede et al., 2022; Yun & Hanson, 2020). Previous research related to customer preferences that affect decision-making on choosing public transportation has found several main indicators that are related to the behavior foundation of customer decision-making. Both parking cost and availability affected customer decision-making in choosing between private and public transportation, a high cost and limited availability of parking, resulting in a tendency to choose public transportation rather than private ((Rayle et al. 2016; Clewlow and Mishra 2017; Grahn et al., 2019). Other findings show that predictable travel time, comfort, and affordability are at the top of considerations (Y. Sunitiyoso et al., 2022; Young et al., 2021; Tirachini and del Rio, 2019).

III. METHODOLOGY

In general, this paper will use a mixed method to identify the customer segmentation of ride-hailing in Indonesia. The purpose of the qualitative research method is to identify and explore the preferences of customers toward their motivation in using a specific ride-hailing service. Through this, the writer hopes to identify a particular variable of preferences (Davids, 2023; Carlini et al., 2023). Afterwards, this paper would like to generalize the specific behavior of customers through their preferences quantitatively (Thanh, 2022; Maciejewski et al., 2019). Ride-hailing industry in Indonesia is still in its growth stage; it is recorded that ride-hailing users in 2023 have reached 65.33 million of the total population around Indonesia (Statista, 2022). Since the research will be separated into two sections, including qualitative and quantitative, the portion of the sample also must be different. Qualitative data collection is more time consuming than quantitative, therefore the portion of sample needed in the analysis is fewer than quantitative. This paper would likely take a minimum range of respondents of 10, aligned with the principal standard (Creswell & Creswell, 2018). However, if the information is not sufficient to answer the variety of consumer preferences, the portion of the sample will be increased. Contrariwise, the sample needed in quantitative research will follow the standard of ratio created by Nunally (1978). The guidance suggests taking a sample based on total items (indicators) at10:1. Since the limited information on a variety of consumer preferences in ride hailing services to build the questionnaire, the author couldn't consider the amount of sample needed yet. The main objective of quantitative research in this analysis is for segmentation analysis, based on preference of factors, and regression analysis, to test whether researchers could find a way to reduce price sensitivity. Later on, the qualitative informants also participated in a quantitative survey.

A) Data Collection Method

For qualitative research, an in-depth interview was conducted. An in-depth interview is one of several qualitative research techniques that have been used to collect data subjectively based on respondents' experience (Rutledge and Hogg, 2020). Later on, this paper will use semi-structured interviews, where there will be a certain kind of topic that will be discussed, with additional spontaneous questions during the interview. The reason is that semi-structured interviews enable the author to dig into an insight that might not be found in a structured question. However, there will be a few questions related to consumer preferences and price sensitivity to enable an explorative approach in the interview, and setting the objective of the interview through crucial questions (Belina, 2023). The author gathered a sample of questions from related articles, several of them are adapted to open-ended questions of explorative approach, while the author himself made other questions.

On the other hand, surveys are the alternative that researchers choose for quantitative data. The design of the survey helps this paper to describe the trend, behavior, and pattern of a population that has been studied in numerical ways, in which the author can generalize a phenomenon. In this research, the type of data that will be used is ordinal data, through a 5-point Likert scale (Likert, 1932). Each variable of consumer preferences will be represented by a group of questions that either have already been implemented by the previous research or come from the qualitative findings.

B) Research Sample

From qualitative data collection, researchers successfully gathered 10 informants. 6 informants are male, while 4 others are female. All informants mostly preferred Grab and Go Jek for commuting, though one informant stated that she usually compared four other applications. The occupations of each informant are quite similar, in which most of them are employees, while several are students and entrepreneurs. On the other hand, quantitatively, researchers can achieve 256 respondents. 55.9% are females, while only 44.1 respondents are male. Most of them are in the range of age between 23-30 years (75.8%) and on average, work as employees (54.3%). For monthly expenses it is quite diverse, range middle expenses, which is Rp 2.500.001- Rp. 5.000.000 takes 26.2% from the population, Rp 1.000.000-Rp 2.500.000 takes 25.8%, and above Rp 7.500.001 takes 24.2% of population. In the preference of ride hailing applications, respondents mostly use Go Jek as the most used ride-hailing application (50%), while the second most preferred is Grab (45.7%).

Table 1: Characteristics of research sample (N = 257)

Category		Frequency	Percent
Gender	Men	113	44.1
	Women	143	55.9
Age	12-22 Years	15	5.9
	23-30 Years	194	75.8
	31-47 Years	46	18
	>47 Years	1	0.4
Occupation	Employee	139	54.3
	Student	71	27.7
	Business Owner	29	11.3
	Housewife/husband	14	5.5
	Doctor	2	0.8
	Teacher/lecturer	1	0.4
Monthly Expenses	<Rp1.000.000	16	6.3
	Rp1.000.000 - 2.500.000	66	25.8
	Rp2.500.001 - 5.000.000	67	26.2
	Rp5.000.001 - 7.500.000	45	17.6
	>Rp7.500.001	62	24.2
Most Preferred Brand	Gojek	128	50
	Grab	117	45.7
	Indrive	5	2
	Maxim	3	1.2
	My BlueBird	1	0.4
	Others	2	0.8

C) Factor Analysis

Before factor analysis, researchers already identified 22 unique factors, most of which are related to the service quality of ride hailing applications both in offline and online aspects. For example, the offline aspect includes comfortless, lead and waiting time, safety, and availability. While the online aspect includes accuracy, features, integration system of application, ease of use in the application; and feature customization order. The researchers also identified other factors related to price and promotion and also reviewed the application. However, since the dimension of factors is too many for the analysis, researchers then reduced the dimension and related it to the E-Service Quality dimension (Thaithakul et al., 2021). In the end, researchers reduced the dimension to 8 factors, namely Price Sensitivity, Ease of Ese, Information Congruity (E-SERVQUAL); Competence (E-SERVQUAL); Platform Responsiveness (E-SERVQUAL), Structural Assurance (E-SERVQUAL); Empathy (E-SERVQUAL); Feature (Appendix 1). From the analysis, the Information Congruity Factor fails to be grouped; thus, the factor is closed for further analysis. In addition, several factors, e.g. PS1, C2, C3; PR1, SA1; SA2, are also terminated due to insufficient model fit scores. The table below presents the final result of factor analysis. The analysis shows sufficient model fit for further analysis, where CMIN/DF should be less than 3, GFI greater than 0.9, RMR below 0.8, AGFI, NFI and TLI in the range of greater than 0.8, and finally, CFI is expected to have values above 0.9. (Dragan, D., & Topolšek, D., 2014; Hu and Bentler, 1999; Wijanto, 2008; Bentler, 1990)

Table 2: Evaluation of Model Fit

Index	Score	Criteria	Source
CMIN/DF	1.834214286	<3	(Dragan, D., & Topolšek, D., 2014)
GFI	0.947	>0.9	
CFI	0.959	>0.9	(Bentler, 1990)
AGFI	0.9	>0.8	(Wijanto, 2008)
TLI	0.933	>0.8	
NFI	0.916	>0.8	
RMR	0.037	<0.8	(Hu and Bentler, 1999)

Table 3: Factor Analysis Result

Variables	Code Items	Items	Factor Loadings
Price Sensitivity	PS2	I am very sensitive to price changes in online ride-hailing services.	0.83
	PS3	I compare prices when booking online motorcycle transportation.	0.515
Ease of Use	EU1	I pay attention to the ease of use of online ride-hailing applications.	0.696
	EU2	I pay attention to the comfort of the interface in online ride-hailing applications.	0.915
Competence	C1	Almost all drivers on the online ride-hailing application I use are competent in providing services.	0.751
	C4	I feel comfortable relying on drivers to reach my destination on the frequently used online ride-hailing application.	0.82
Platform Responsiveness	PR2	The online ride-hailing application I frequently use is usually quick to respond to my needs.	0.588
	PR3	I often encounter errors when searching for transportation services on the online ride-hailing application I frequently use.	0.986
Structural Assurance	SA3	I trust the security system and technology within the ride-hailing application I frequently use for online transactions.	0.821

	SA4	Generally, the ride-hailing application I frequently use is sufficiently strong and secure for online transactions.	0.858
Empathy	E1	I feel that all drivers on the online ride-hailing application I frequently use behave according to the passengers' wishes.	0.843
	E2	When passengers need assistance, almost all drivers on the online ride-hailing application I frequently use will do their best to help.	0.762
Feature	F1	There is a specific feature that I use in the online ride-hailing application, which makes me more inclined to choose that application.	0.669
	F2	Features are one of the reasons I use a particular online ride-hailing application.	0.814

D) Cluster Analysis

Segmentation is a set of groups that have similarities in characteristics; thus, it is aligned with clustering analysis. In this case, the usage of cluster analysis in common is to find identical patterns of data sets. In defining segmentation, there are two stages of analysis. Firstly, the researcher's objective is to find the number of clusters from hierarchical cluster analysis. Later on, non-hierarchical cluster analysis would proceed to see the pattern of behavior from each factor of importance. In processing hierarchical cluster analysis, researchers use a specific R package, namely NbClust to see a suitable number for the cluster (A. Maggio, 2020). NbClust uses 30 indices and will automatically choose the suitable number based on the majority of analysis from those indices. Due to its limitation, it is highly recommended to use other classification methods as complementary (Everitt et al., 2011). In this case, the paper uses the non-hierarchical method. Since the non-hierarchical approach needs a fixed number of clusters, the number of segments generated from 30 indices will be used. K-means clustering in a non-hierarchical approach was applied due to its popularity (Amlan et al., 2021) and applied agglomeration coefficient with Ward's method. Researchers later on found a suitable number for segmentation 4 from NBClust analysis; next, due to convenience of use, researchers decided to use IBM SPSS Statistics 26 Program for K-means analysis.

Table 4: Final Cluster Centers

Factors	**Cluster**			
	I	**II**	**III**	**IV**
Price Sensitivity	-1.076377453	0.2343718633	0.2156778134	0.1841701958
Ease of Use	-0.3257005648	-0.1009301981	0.06949195199	0.2120619209
Competence	0.02330564103	-0.4280430966	-0.1681506467	0.50167104
Platform Responsiveness	-0.3485868526	-0.3234618483	1.903621753	-0.8449108734
Structural Assurance	-0.1084102221	-0.3056774843	-0.08652512924	0.3989835428
Empathy	0.1210346043	-0.5533727212	-0.06852566793	0.4985223964
Feature	-0.410763348	-0.3196907423	0.2684118987	0.3201107171

From the non-hierarchical cluster analysis, it is found that Cluster 4 has the greatest number of observations, followed by Cluster 2, 3, and 1 in order. Here is the size of the cluster presented in Table 6.

Table 5: Size of Clusters Obtained

Segments	**Name**	**Number of Observations**	**Percentage**
I	Service-Excellence Seekers	42.00	16.34%
II	Price-Priority Users	76.00	29.57%
III	App-Centric Users	57.00	22.18%
IV	Seamless Experience Seekers	82.00	31.91%
Valid		257.00	100.00%
Loses		0	0.00%

E) Regression Analysis

The objective of linear regression is to test whether it is possible or not to reduce the price sensitivity dimension from the customers. From qualitative findings, it is found that price sensitivity could be reduced by other factors or the individual is already attached to certain applications. Even if it is slightly higher, the individual would rather choose certain applications based on their preference.

"If there is a significant difference, we'll definitely go for it. Of course, it's human nature. We want to save. If the difference isn't significant, then I'll just stick with the ride-hailing app I use most frequently."- DK.

This desired result from the analysis is an inverse relationship between independent and dependent variables, with significant effect. By definition, linear regression is a statistical technique to test the model linear relationship between dependent and one or more independent variables (W. Hsieh, 2023). The negative relationship between the independent variable(s) and dependent variable reflects that if the independent variable(s) is/are increasing, the dependent variable will be decreasing (Aggarwal & Ranganathan, 2017). Thus, this technique is suitable for the analysis. The accepted hypothesis from this analysis is when the significance level <0.05, while the coefficient level is below zero. The minimum size of linear regression from the guidance proposed by G. David & Jenkins (2020) is actually N>8, though to increase the variance, it is superior to have N>25. The regression analysis is conducted for Cluster 2, Cluster 3, and Cluster 4, while Cluster 1 is found to be not price sensitive.

Table 6: Coefficients of Cluster 2

Factors	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
Ease of Use	0.081	0.158	0.089	0.511	0.611
Competence	0.198	0.274	0.194	0.722	0.473
Platform Responsiveness	-0.056	0.069	-0.095	-0.81	0.421
Structural Assurance	0.083	0.312	0.059	0.266	0.791
Empathy	-0.198	0.147	-0.234	-1.347	0.183
Feature	0.05	0.094	0.084	0.532	0.596

Cluster 2, with the factor that is positive coefficient only in price sensitivity, showed insignificant results of other variables that affect the price sensitivity. This is reasonable and related to Table 5.

Table 7: Coefficients of Cluster 3

Factors	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
Ease of Use	-0.075	0.183	-0.057	-0.412	0.682
Competence	-0.323	0.236	-0.372	-1.369	0.178
Platform Responsiveness	-0.002	0.109	-0.002	-0.015	0.988
Structural Assurance	1.229	0.34	1.16	3.616	0.001
Empathy	-0.646	0.197	-0.886	**-3.276**	**0.002**
Feature	0.405	0.147	0.382	2.754	0.009

The analysis focuses on the coefficient and significance. The negative coefficient represents the inverse relationship between two variables. It can be seen in Cluster 3 that empathy has a negative coefficient and significantly affects price sensitivity. This means that if the factor of empathy is increasing, the price sensitivity will be decreasing.

Table 8: Coefficients of Cluster 4

Factors	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Ease of Use	-0.492	0.232	-0.344	**-2.117**	**0.038**
Competence	0.168	0.39	0.12	0.431	0.668
Platform Responsiveness	0.062	0.084	0.099	0.737	0.463
Structural Assurance	0.587	0.454	0.377	1.294	0.2
Empathy	-0.633	0.17	-0.582	**-3.73**	**0**
Feature	0.078	0.163	0.075	0.476	0.636

The cluster which has the most observed number, which is Cluster 4, showed an interesting result. The Price Sensitivity could be reduced from 2 other variables, which are the Ease of Use of the application and the empathy that the brand gives through the driver. The most significant factor in this case is correlated with Cluster 3, which is empathy.

IV. ANALYSIS OF RESULTS

Dominated by men (52%), segment 1, called "Service-Excellence Seekers", is the only segment that is not price sensitive. In addition, this type of segment has the least population among the three other segments. From the demographic profile, 54% of them work as employees, 29% are students and only 19% work as businessmen or entrepreneurs. From monthly expenses, this type of segment has the majority of highest spending per month which is higher than Rp 7.500.001 for about 33% of the group, while only 2% are spending less than Rp 1.000.000. The main goal that needs to be solved by this segment through using ride-hailing applications is mostly for the working activity, whether they need to be able to reach their workplace immediately or reach their clients. Researchers identified two informants from qualitative interviews as a part of "Service-Excellence Seekers". It is identified from both interview and cluster analysis that the price is not their main consideration. However, they need a service that is always available at any time and under every condition to fulfill their job that needs to be done. That is why, to know the quality of service provided by a ride-hailing application, they usually do a comparison of quality, whether from previous experience or do a quick comparison by testing more than one application to know the competence of ride-hailing providers. The evaluation of a ride-hailing application can be reflected from previous experience or quick testing of competence by ordering more than one application and doing a quick cancellation if the application is unable to fulfill the requirement or another application has a faster drive.

Furthermore, this kind of service experience is affecting the behavior of decision-making in the future. The Empathy factor is one of the important evaluations for this segment. The unfavorable experience related to the driver's emotion toward its customers will affect their decision-making in the future, in which they will less prefer the application that gave them a bad experience emotionally.

Segment 2, which can be called a "Price-Priority Users", is dominated by women with a percentage of 65%, while men are only 35%. This type of segment has a majority of medium monthly expenses (27%), with the range of Rp 2.500.000,00 - Rp 5.000.000,00. The occupation that is dominated by this segment is similar to segment one with a percentage of 59%, though there are several housewives in this segment (7%). This type of segment is the most efficient segment among other segments. Researchers only identified one informant as part of Segment 2. The reason why she uses a ride-hailing application is usually to avoid congestion and reach the destination faster; thus, they usually use motor-bike service rather than a car. Not only do they want to reach their specific destination and avoid congestion, but also, they want to save or lower their cost down. In evaluating among alternatives to ride-hailing services, they tend to do a comparison of prices in order to see the cheapest option among applications with the same destination and location. In this case, these individual uses four different applications (with a probability of using more options if there are more ride-hailing applications. The reason behind choosing the cheapest option reflected their perspective about public transportation since the usage of public transportation is to save more money by using it thus if public transportation is more pricey than private transportation, there is a probability that this type of segment uses more private transportation rather than public transportation.

There is a similarity in the majority income with segment 1 (31%); this segment is dominated by females (57%). An "App-Centric Users", a name given to segment 3, is a price-sensitive segment in which they consider price as one of the factors in choosing a ride-hailing service. However, through the analysis of this type of segment is quite possible to reduce the consideration price by increasing other factors. Most people in this segment work as employees, with a percentage of 54%.

There is only one representative from segment 3, who is a male. Mostly, these individuals use ride-hailing applications for work, especially reaching the client. The reason why he doesn't use private transportation is that he sometimes has a meeting while traveling, which is possible when using ride-hailing applications.

Interestingly, this individual uses a specific app in just one application, which is a rental feature that is mostly used when traveling far distances. Since this segmentation is named "App-Centric User", thus ease of use of applications is another important factor. The ease of use of the application is evaluated by an efficient system that can cut down a certain uncertainty process, which affects the decision-making.

The last and the most dominant segment is called the "Seamless Experience Seekers". Dominated by men (51%), this segment has the majority (31%) of the smallest monthly expenses compared to other segments, though the comparison with monthly expenses above Rp 7.500.000,00 is not significant (24%). Like other segments, segment 4 is dominated by employees (48%), though it's quite diverse in terms of occupation. In this case, the reason why segment 4 uses ride-hailing is because of their daily routines, whether commuting to work or traveling around the city. Segment 4 is also the part among segments that is price sensitive, though price is not only their consideration in choosing ride hailing applications. A male is a representative informant of this segment. Although he knew a certain application offered a cheaper option, though, since the comfortless and competent service quality offered by that application didn't meet his expectation, it affected his decision-making of choosing a ride-hailing application; even Maxim was "blacklisted" from his alternative ride-hailing application. This reflects that although segment 4 is price sensitive if the service delivery made by the provider does not meet their expectation, they would choose another application, even though it is the cheapest option. Other than that, the ease-of-use application also affects the decision-making, even if it becomes a pain if the pickup location is not accurate since the customer must put more effort into describing the location to the driver. The informant also "blacklisted" certain applications because of empathy delivered by the driver (showing unpleasant emotion). This affects the next decision-making of choosing a ride-hailing application, which creates an unpleasant experience for them, resulting in neglecting or abandoning the offering from the ride-hailing provider.

VI. RECOMMENDATION

From both regression and cluster analysis, it can be found that ease of and empathy are two factors of consideration for this segment, and can even reduce the consideration in price if both aspects are superior. From segment 4's case, it can be seen how he neglects the offering of certain (even though it is cheaper) and chooses another application as his main preference since the "blacklisted" application is unable to meet his expectation on factors of empathy and ease of use. It is confirmed that every segmentation has its own priority of factors that affect the decision-making of a purchase (Aksu et al., 2020). In this case empathy is one of the most significant for decision-making in choosing ride-hailing service. In detail, the "service-excellence seeker" has a top priority of factors in the empathy that the driver gives, this includes how the drivers understand them and try to be aligned with their emotions. In addition, empathy is also found to have a significant impact on reducing price sensitivity for two segments.

On the other hand, ease of use is also found to have a significant effect on the decision-making of two segments, which are the "App-Centric User" and "Seamless Experience Seeker". Since the App-Centric User's priority is in the features of the application, the ease of use helps them to have a smooth experience while using the application and the features of service from the service provider. Contrariwise, "Seamless Experience Seeker" wants to have a seamless experience in both offline and online service, which is why ease of use is included in the consideration to boost a favorable experience during the consumption of service. Lastly, it is found that competence is also an important factor. Two segments were found to tend to evaluate the competence of drivers, and this will affect the next decision-making of choosing a ride-hailing service among alternatives, in which, if the previous experience was unfavorable for them, they will probably not use the same service.

Later on, it is a must to discuss the reason why empathy affects price sensitivity. Firstly, although the "App-Centric User" is heavily focused on the features of an application, it also found that empathy has an indirect effect on the next decision-making of using ride-hailing services. The informant of segment 3 describes that if he has a wonderful experience and if he finds that the driver is suitable enough (emotionally) for him, he will use the same application even with the same driver. Successful service delivery, especially when the driver fulfills the passenger's needs can affect the next decision-making of customers in choosing ride-hailing service among alternatives. This is the case; he shows a desire to use the same driver in the same application, and this means that price is not his consideration anymore since he found a suitable driver to accompany him while traveling. This experience is aligned with the discussion made by Kotler Keller (2020). It is stated that the satisfaction resulting from the buying process, will make a high chance that consumers consume more of the same product or service. A contrast experience can be found in the representative of "Seamless Experience Seekers". Empathy has also been tested to have a significant effect on reducing price sensitivity; even this segment thinks that empathy is one of the impactful factors in choosing the right service.

On the other hand, ease of use can reduce the price sensitivity only in one segment. The seamless experience seeker, who considers the whole aspect of experience while using the application and the service, is shown to have a probability of neglecting the price while in the decision-making stage of choosing a ride-hailing service. Related to the statement of one informant, the representative of segment 4, the bad experience resulted from the combination of lacking empathy and bad user experience, which can be seen as a fallacy of accuracy of pick-up, resulting in a chaotic experience of representative segment 4. From the interview, researchers can only identify the pain experience, which results in ignoring the provider's service even if they are the cheapest possible option. Ease of use itself reflects the convenience of use, or some informants call it "user friendly". From the information of the interview of segment 4, it was stated that the factor that affects him in decision making is the convenience of use and the price. Logically, since he is a part of the price sensitive segment, he will use an application that is cheaper. However we know that he neglects the price because of two factors, and one is related to the ease of use in application. In addition, we can see that the brand preferred by him is more convenient to use and has accurate pickup points. Thus, since the ease of use in that application is high, he neglects the offering from other applications that are cheaper.

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APPENDIX

Appendix 1. Survey Questions

Indicator = 25 Items		
Variables	**Items**	**Sources**
Price Sensitivity	I notice the prices of online ride-hailing services every time I make a booking.	Cao, Y., & Wang, J. (2024).
	I am very sensitive to price changes in online ride-hailing services.	
	I compare prices when booking online motorcycle transportation.	Self-Developed From Interview
Ease of Use	I pay attention to the ease of use of online ride-hailing applications.	Loh, H. S., Lee, J. L., Gu, Y., Chen, H. S., & Tay, H. L. (2024).
	I pay attention to the comfort of the interface in online ride-hailing applications.	
Information Congruity	The online ride-hailing application I frequently use usually provides services that align with the stated information.	Thaithatkul, P., Anuchitchanchai, O., Srisurin, P., Sanghatawatana, P., & Chalermpong, S. (2021).
	The online ride hailing application I frequently use often lacks consistency in providing information matching the original offers.	
	The online ride-hailing application I frequently use always matches the description provided.	
Competence	Almost all drivers on the online ride-hailing application I use are competent in providing services.	
	I am always confident in relying on drivers to reach my destination on the frequently used online ride-hailing application.	
	I feel that all online ride-hailing drivers compete in providing services.	
	I feel comfortable relying on drivers to reach my destination on the frequently used online ride-hailing application.	
Platform Responsiveness	The online ride-hailing application I frequently use is usually quick to respond to my needs.	

Indicator = 25 Items		
Variables	**Items**	**Sources**
	I often encounter errors when searching for transportation services on the online ride-hailing application I frequently use.	
	The online ride-hailing application I frequently use does not respond accurately to my needs.	
Structural Assurance	The ride hailing application I often use provides sufficient security, making me feel comfortable.	
	I feel confident in the adequate legal framework to ensure my safety while using the ride-hailing application.	
	I trust the security system and technology within the ride-hailing application I frequently use for online transactions.	
	Generally, the ride-hailing application I frequently use is sufficiently strong and secure for online transactions.	
Empathy	I feel that all drivers on the online ride-hailing application I frequently use behave according to the passengers' wishes.	
	When passengers need assistance, almost all drivers on the online ride-hailing application I frequently use will do their best to help.	
	Almost all drivers on the online ride-hailing application I frequently use not only act according to their own desires but also prioritize their passengers.	
Feature	There is a specific feature that I use in the online ride-hailing application, which makes me more inclined to choose that application.	Self-Developed From Interview
	Features are one of the reasons I use a particular online ride-hailing application.	