A Study of Perceived Value in the Ride-Hailing Transportation Sector in Jakarta

Alexander Wollenberg and Lidia Waty

***Abstract*—The article examines the effectiveness of promotion on repurchase intention by perceived value and transportation mode preferences. The method of analysis of this research is structural equation modeling (SEM) based on cluster sampling in Jakarta. The findings of this research are: price promotion and other 7Ps marketing mix elements have significant direct effects on perceived value. The strong factors among those are price-promotion and process factors. Perceived value has a significant direct effect on transportation mode preferences and subsequently on repurchase intention. However, price promotion and other 7Ps in the marketing mix do not have a significant direct effect on transportation mode preferences for the use of Indonesian public motorcycles called *Ojek* and the booking process via ride-hailing apps.**

***Index Terms*—Marketing mix, perceived value, repurchase intention, SEM, startups, transportation.**

I. INTRODUCTION

The recent phenomenon of mobility in Jakarta is assisted by the public transportation that the whole process of service is mediated through smartphone ride-hailing apps. The unavoidable needs of fast mobility in the capital city of Jakarta is an advantage for startup companies to change the business model of *Ojek*. *Ojek* has been known for years in Indonesia as non-formal for-hire mode of public transportation in the form of riding pillion on motorcycles. The article examines the effectiveness of promotion on repurchase intention through perceived value and transportation mode preferences.

The method of analysis of this research is structural equation modeling (SEM) based on cluster sampling in Jakarta. The findings of this research are: price promotion and other 7Ps marketing mix elements have significant direct effect on perceived value. The strong factors among those are price-promotion and process factors. The perceived value has significant direct effects on transportation mode preferences and subsequently on repurchase intentions. However, price promotion and other 7Ps of the marketing mix do not have significant direct effects on transportation mode preferences.

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II. THE ORETICAL FRAMEWORK

A. Relation between Price Promotion and Perceived Value

One of the expressions of perceived value from customers in services marketing according to [1] and [2] is "Value is low price". This concept is utilized by startup companies in order to determine the fare for a ride by non-traditional *ojek* (booked via ride-hailing app) which is cheaper than the price of a traditional *ojek* (flagged on the street). The perceived value and the fare can vary by customer, particularly in different parts of Jakarta which can be far and difficult to access due to traffic jams and distances.

Promotions are thus indispensable marketing activities widely used by startups in order to increase awareness of and encourage people to use the service. Promotional strategies can consist of many techniques to deliver the message of a useful service the startup offers to the customer. Promotional strategies in non-traditional *ojeks* include free credit for first-time users and lower prices compared to traditional *ojeks* (those hailed on the street).

Based on the theory of perceived value, we posit that price and promotion as the first marketing strategies of startups have significant direct effects on customer perceived value related to monetary costs.

- Hypothesis 1:Price Promotion has a significant direct effect on customer perceived value

B. Relation between other 7Ps Marketing Mix Elements and Perceived Value

The non-monetary aspect of perceived value mentioned by [2] relates to other factors of service, such as mobility, waiting time and the environment in which the service takes place. The perception of "value" of service causes customers to respond towards service both positively and negatively.

- Hypothesis 2: Other factors in 7Ps of the marketing mix have a direct positive effect on customers' perceived value

C. Relation between Perceived Value and Transportation Mode Preferences

Recent evidence by [3] provides direct support for the causal link between customer perceived value and preferences.

- Hypothesis 3:Customer perceived value has a direct effect on transportation mode preferences

D. Relation between Price Promotion and Transportation Mode Preferences

Price promotion can have positive or negative effects

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towards customer preferences depending on attribution and precise information of the product or service characteristics.

- Hypothesis 4: Price promotion has a direct effect on transportation mode preferences

E. Relation between other 7Ps Marketing Mix Elements and Transportation Mode Preferences

The positioning strategy of a firm is determined through the target customers, competitors and the company's own competitive advantage. This positioning strategy aims to adjust the product or service to the preference in the different segment [4].

- Hypothesis 5: Other 7Ps Marketing mix elements (People, Process, Place, Product [Service], Physical Evidence) have direct effects on transportation mode preferences

F. Relation between Transportation Mode Preferences and Repurchase Intention

The result of the study of the general equation model of repurchase intention by [3] reveals that perceived value is the main factor influencing preference of customers since it has a significantly higher path coefficient in the model.

- Hypothesis 6: Transportation mode preferences have a direct positive effect on customers' repurchase intentions.

According to the explanation for each relation of research variables, the framework below summarizes factors that influence repurchase intentions:

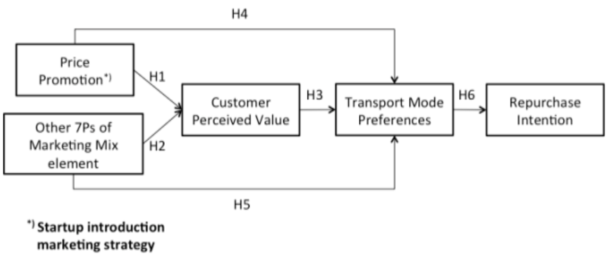

Fig. 1. The framework price-promotion towards repurchase intention.

III. STRUCTURAL EQUATION MODELING

Structural Equation Modeling (SEM) is "multivariate technique combining aspect of factor analysis and multiple regression that enables the researcher to simultaneously examine a series of interrelated dependence relationships among the measured variables and latent constructs as well as between several latent constructs" [11]. Moreover, SEM is generally used in the behavioral sciences as a structure for covariance between the observed variables and therefore it is known as covariance structure modeling. The visualization of structural equation models usually in the form of graphical *path diagram* and the statistical model is represented in a set of matrix equations.

There are two categories of variables in SEM, observed and latent. Theoretical constructs in Structural Equation Modeling are represented by the latent factors. Observed variables or manifest variables are used as an indirect measure or indicator of latent variables [5]. Meanwhile, latent variables in SEM correspond to hypothetical constructs or factors that are not directly measured and cannot be observed. Rather, other dimensions called observed variables represent the latent variable. Furthermore, in SEM model, there is categorization of latent variables: exogenous and endogenous latent variables. Exogenous variable refers to independent variables and endogenous variable refers to the dependent (outcome, criterion) variables in model diagrams. Another variable in SEM is related to residual or error terms that associated with either observed variables or latent variables [6].

A. SEM Characteristics

Ref. [9] points out that Structural Equation Modeling is distinguished from other multivariate techniques due to the following characteristics:

1. The presence of construct as unobservable that is represented by observed variables in dependence relationships.
2. Estimation of multiple and interrelated dependence relationship incorporated in an integrated model.
3. A hypothesized dependent variable can become an independent variable in subsequent dependent relationship.
4. Explanation of the covariance among the observed variables. In addition, "SEM seeks to represent hypotheses about the means, variances, and covariance of observed data in terms of smaller number of structural parameters defined by a hypothesized underlying model" [6].

B. Why Use SEM?

According to the characteristics above, the research model that is depicted on Fig. 10 would be best measured by structural equation modeling. There are three reasons why it is chosen as best method of analysis for this research:

- The strong reason for using structural equation modeling is because researchers are becoming more aware of the need to use multiple observed variables to describe its latent variables and it is incorporated in SEM models. Variables (price promotion, other 7Ps marketing mix element, customer perceived value, transportation mode preferences and repurchase intention) in this research are latent variables that are measured by observed variables. In addition, there are multiple observed variables to better understand the research construct of latent variable.
- Based on the second and the third characteristic of "Estimation of multiple and interrelated dependence relationship incorporated in an integrated model" [7], there are some hypothesized dependent variables become an independent variable in subsequent dependent relationship in the model. For instance, customer perceived value is dependent variable of price promotion and other 7Ps marketing mix element, yet, it is the independent variable for transportation mode preferences in the model. Moreover, SEM is chosen over multiple regressions because the measurement of more than one dependent variable using multiple regressions should be performed in analysis separately. Nevertheless, SEM enables the ability of evaluating model construct relationships simultaneously [8].
- SEM provides explicit estimates of error variance

parameters meanwhile other multivariate techniques are not capable of assessing or correcting the measurement error [9]. It is useful for this research to assess and correcting the measurement error for each observed variables in order to be capable for modeling multivariate relations, either direct and indirect effects of variables in the model to minimize the possibility of incorrect conclusion because of misleading regression estimates.

C. Procedure of SEM

According to Kline (2011), there are six basic steps are followed in most analysis that is depicted in the following figure:

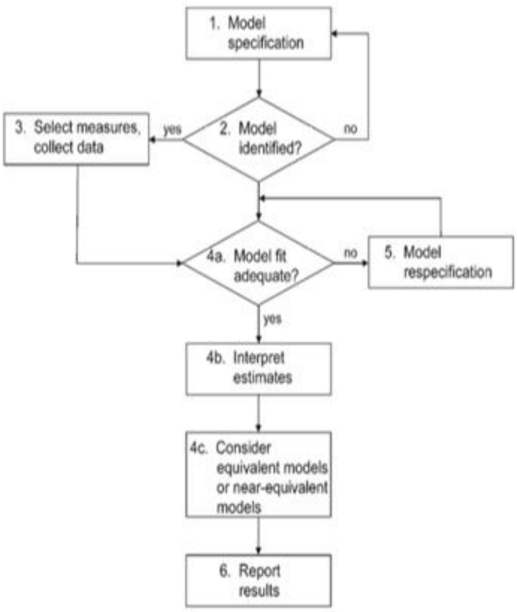

Fig. 2. General steps in structural equation modelling (Kline, 2011).

IV. Research Methodology and Findings

A. Sampling Design and Technique

According to [9], sampling design process in marketing research consists of five stages: define target population, determine the sampling frame, select a sampling technique(s), determine the sample size and execute the sampling process. [10] points out "Population or universe is any complete group of entities that share some common set of characteristics". Information about population parameters can be obtained by taking a census or a sample. "A census involves a complete enumeration of the element of a population", meanwhile, "a sample is a subgroup of the population selected for participation in the study" [9]. In this research, the population refers to all non-traditional *ojek* users who are actively using the non-traditional *ojek* service to accommodate their daily activities regularly.

B. Sampling Frame

In Jakarta, some startups (*Gojek* and *Grabbike*) mentioned there are 1.5 and more than 5 million non-regular basis users [11]. The sampling frame were non-traditional *ojek* passengers in different areas of Jakarta.

C. Sampling Technique

Specifically, cluster sampling is used in order to ensure the coverage and reflect the population of Jakarta based on the criteria used for each area. The sample in this research would be divided into five strata: North Jakarta, West Jakarta, East Jakarta, Central Jakarta and South Jakarta. The advantage of this technique is a "smaller standard error may result from this cluster sampling because the groups will be adequately represented when strata are combined" [12]. Afterwards, the sample is chosen randomly for each area in Jakarta.

D. Scale Reliability and Validity

In terms of goodness of data, there are two criteria to evaluate it: reliability and validity of the measures. Reliability of a measure is built through testing for consistency and stability. Both concepts refer to the term of how well the items are measured and converged on the same result. "Cronbach's Alpha is a reliability coefficient that indicates how well the items in a set are positively correlated to one another" [13]. In addition, [13] point out that Cronbach's Alpha is calculated based on the average inter correlations among the items when measuring the concept and further they state, "The closer Cronbach's Alpha is to 1, the higher the internal consistency reliability". In general, [14] explain that coefficients alpha between 0.80 and 0.95 are considered to have very good reliability. Moreover, the acceptable value of Cronbach's alpha is 0.7-0.8 in order to indicate a reliable scale. Meanwhile, the value of Cronbach's alpha less than 0.6 is considered unreliable. Other measurements to evaluate the reliability and validity of the model are composite reliability and average variance value. The following is the explanation for each:

E. Composite Reliability (CR)

Ref. [9] argues that CR is defined as the total amount of true score variance in relation to the total score variance and it is calculated as follows:

$$CR = \frac{\left(\sum_{i=1}^{p} \boldsymbol{\lambda i}\right)^2}{\left(\sum_{i=1}^{p} \boldsymbol{\lambda i}\right)^2 + \left(\sum_{i=1}^{p} \boldsymbol{\delta i}\right)}$$

CR = composite reliability
λ= completely standardized factor loading
δ = error variance
p= number of indicators or observed variables

F. Variance Extracted (VE)

AVE is calculated in terms of the (completely) standardized loadings as follows:

$$AVE = \frac{\sum_{i=1}^{p} \boldsymbol{\lambda i}^2}{\sum_{i=1}^{p} \boldsymbol{\lambda i}^2 + \sum_{i=1}^{p} \boldsymbol{\delta i}}$$

AVE = average variance extracted
λ= completely standardized factor loading
δ= error variance
p= number of indicators or observed variables

V. Data Analysis and Findings

A. Methodology

Based on the framework of Structural Equation Modelling, our data analysis consists of the following steps: Model Specification, Model Identification, Data Screening, Model Estimation – Measurement and Structural Model Fit, Model Re-specification and Interpretation.

B. Model Specification

Structural Equation Modelling consists of two main parts: the measurement model and the path model. "The measurement model represents a set of *p* observable variables (manifest variables) as multiple indicators of a smaller set of *m* latent variables, which are usually common factors" [15]. In the study, there are five latent variables and 18 manifest variables in total.

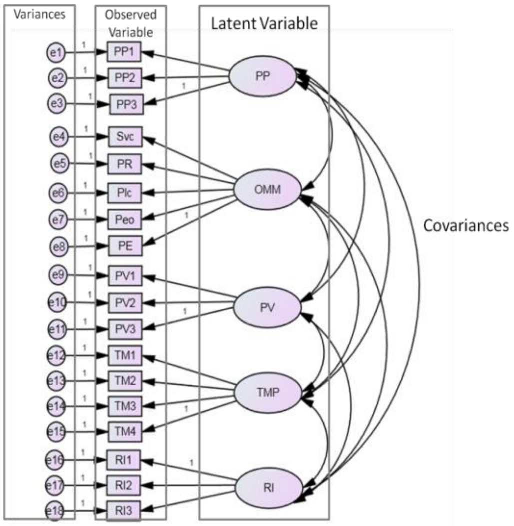

Fig. 3. Path diagram of initial measurement model.

Meanwhile, the path model (structural model) is used to describe relations of dependency which are usually accepted to be in causal relationships between the latent variables [6]. The relationship between latent variables and their indicators (recursive relationship because it has a single direction) is illustrated in Fig. 3.

The critical ratio obtained by dividing the covariance estimate by its standard error for significance level of 0.05, critical ratio that Moreover, the result of structural model test in this research is illustrated in Fig. 4:

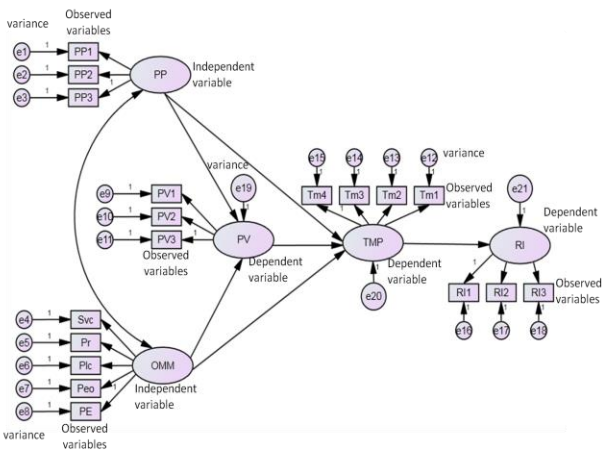

Fig. 4. Path diagram of initial structural model.

C. Model Identification

Model identification is initiated with the comparison of the number of available data and the number of estimated parameter. The number of the available data is based on the formula $[(n*(n+1))/2]-k$, where n is the number of manifest variable and k is a sum of regression coefficient, error variance and covariance between latent variable [15]. This step is done to ensure the model is over-identified and therefore it is eligible to conduct further analysis. An over-identified model occurs when the number of data points is greater than the number of parameters to be estimated.

VI. Hypothesis Testing

The structural equation analysis is based on the calculation of path coefficient and an R^2 which resulted from the research model, in particular for structural model test. In addition, regression weight for each construct will determine the hypothesis decision through *p* value [14]. Furthermore, square multiple correlations (R^2) is evaluated as independent of units of measurement for each endogenous variables [13], [14], and [15]. The *p* value and critical value (known as the t-value) of each construct relation is determined through the Regression Weight section in the AMOS program.

VII. Conclusion

Based on the result of this study, price promotion has an effect on repurchasing intentions for non-traditional *ojek* through perceived value (monetary and non-monetary) and thus consequently affects transportation mode preferences. The evidence is based on the path coefficient of price promotion and the other 7Ps of the marketing mix which positively affect perceived value (indicated by the positive sign with values of 0.5 and 0.2 as path coefficients). Moreover, perceived value positively affects transportation mode preferences (marked by a positive value of 0.651 for the path coefficient). Furthermore, transportation mode preferences positively affect repurchase intentions (value is 0.51 for path coefficient). This finding confirms the result of the study of the general equation model by [16] as they reveal that perceived value is the main factor influencing preferences of customer purchasing decisions since it has a significantly higher path coefficient in the model of repurchase intention.

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