LONGITUDINAL MODELING OF E-COMMERCE CHOICE USING LATENT GROWTH CURVE TO ASSESS INFLUENCING FACTORS AMONG LATE ADOLESCENTS

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Abstract

The rapid growth of e-commerce in Indonesia has significantly influenced consumer behavior, particularly among late adolescents aged 18–21 years. This study examines the dynamic factors affecting e-commerce preferences, including price, service quality, and customer loyalty, using Latent Growth Curve Modeling (LGCM). This method was chosen for its ability to analyze variable changes longitudinally, allowing the identification of growth patterns and factors influencing shifts in consumer behavior over time. Data were collected through an online survey involving 400 respondents over three time periods. The study's findings reveal that price is the most stable variable (intercept 0.5302, slope 0.0811), whereas service quality (intercept 0.8127, slope -0.0285) and loyalty (intercept 0.8508, slope -0.0188) show slight declines. Innovation, functioning as a covariate, significantly affects the intercept of all variables, particularly loyalty, although its impact on growth rates varies. The model demonstrates a good fit, with RMSEA (0.0730), CFI (0.9844), and TLI (0.9402), confirming its validity. Visualizations indicate that loyalty evolves more dynamically than service quality, highlighting the crucial role of innovation in customer engagement. This study emphasizes the need for e-commerce platforms to prioritize innovation and service quality improvements to foster long-term loyalty. These findings provide valuable insights into consumer behavior dynamics and offer strategic recommendations for achieving competitive advantage in the digital marketplace.

Keyword: *Latent Growth Curve Modeling, E-commerce, and Consumer Behavior.*

INTRODUCTION

In the digital era, advancements in information technology have significantly impacted businesses, particularly through innovations such as e-commerce, which has become a dynamic virtual transaction platform (Chen, Luo, & Tong, 2024). E-commerce drives businesses to enhance their competitive advantage and facilitates global production and trade, with a significant increase in online retail sales volume. In Indonesia, social commerce is growing rapidly due to the adoption of digital models by businesses, supported by an internet penetration rate of 79.5% in 2024 (Huwaida, et al., 2024). However, e-commerce faces challenges in maintaining customer loyalty, understanding purchasing behavior, and adapting to dynamic consumer preferences. Advancements in the quick commerce sector, such as instant delivery for online shopping, have also expanded business services in the online market. To remain competitive, businesses must innovate, understand the factors influencing loyalty, and manage purchasing behavior by considering antecedents and moderating factors.

Several studies indicate that while many researchers have identified factors influencing e-commerce selection, the use of Latent Growth Curve Modeling (LGCM) remains limited. Oktavia, et al. examined the impact of electronic service quality and security seals on customer satisfaction and loyalty in Shopee using SEM, but their study was limited to a single platform (Oktavia, Warsito, & Kadarrisman, 2023). Putri & Pratama identified factors such as service quality, product quality, security assurance, features, promotions, and emotional value in consumer satisfaction among students using e-commerce in Padang City but did not explore the quantitative impact of each factor in depth (Putri & Pratama, 2024). Rodriguez applied LGCM and regression to analyze the reduction of social anxiety due to well-being and concerns but faced limitations related to bias and generalization (Rodriguez , 2023). Unlike static analyses, LGCM evaluates dynamic changes in variables, providing deeper insights into factor interactions over time. This study utilizes LGCM to explore the impact of price, quality, and loyalty, with innovation as a covariate, contributing to the understanding of e-commerce selection factors.

This research aims to analyze the factors influencing e-commerce selection among late adolescents, a crucial demographic in the digital market. The primary focus is to explore the impact of price, loyalty, quality, and technological innovation on consumer behavior, particularly among late adolescents aged 18 to 21 years. Using Latent Growth Curve Modeling (LGCM), this study will analyze the dynamic changes of these factors over time, offering a deeper understanding of their long-term effects. Additionally, this research aims to provide practical insights for e-commerce platforms to optimize their services based on a clearer understanding of evolving consumer preferences. The findings from this study are expected to enrich the existing literature on e-commerce and consumer behavior while helping businesses adjust their marketing strategies in an increasingly competitive market.

RESEARCH METHODS

1. Research Variables and Data Sources

This study measures several variables longitudinally over three different time periods across three months, specifically in August, September, and October 2024. The analyzed variables include:

Table 1. Research Variables

Variable	Description
Price	The extent to which the price corresponds to the received product on the selected e-commerce platform in the first, second, and third months.
Quality	The extent to which the quality of the received product meets expectations on the selected e-commerce platform in the first, second, and third months.
Loyality	The likelihood of continuing to use the selected e-commerce platform in the future during the first, second, and third months.
Innovation	The frequency with which the selected e-commerce platform introduces new products or technological innovations as an external variable or covariate.

Each question in the questionnaire uses a Likert scale ranging from 0 to 10, where a value of 0 indicates very low agreement or dissatisfaction with the measured aspect, while a value of 10 reflects a very high level of agreement or satisfaction. This scale allows for a more detailed analysis of respondents' perceptions of each research variable. The data for this study was collected through a questionnaire distributed via Google Forms. The questionnaire was designed to measure variables such as price, service quality, loyalty, and innovation related to e-commerce platforms. This study successfully gathered data from 400 respondents, all of whom were late adolescents aged between 18 and 21 years. Respondents provided answers based on their experiences and perceptions of the e-commerce services they used, ensuring that the collected data reflects the perspectives of this age group regarding the factors influencing their e-commerce selection.

2. Analysis Steps

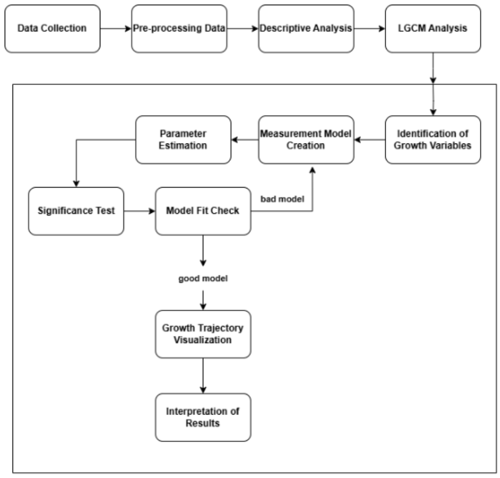

Figure 1. Flowchart

2.1 Data Collection

The data for this study was collected through an online questionnaire distributed via Google Forms, involving 400 respondents who were late adolescents aged between 18 and 21 years. Measurements were conducted in stages over three months, beginning in August, followed by September, and concluding in October. The sample size was determined using Slovin's formula:

$$n = \frac{N}{1+N*(e^2)} \tag{1}$$

Where *N* is the population size, and e^2 is the square of the margin of error (0.05).

Subsequently, data validation tests were conducted, including validity and reliability tests. The validity test utilized the Kaiser-Meyer-Olkin (KMO) measure, which assesses the adequacy of questionnaire items. This test aims to determine whether the items can be used in factor analysis to compute the loading factor (Hakim & Mulyapradana, 2020). The KMO formula is as follows:

$$MO_j = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} u} \tag{2}$$

Where r_{ij}^2 represents the squared correlation between variables, and *u* denotes the partial correlation between variables.

Table 2. KMO Value Acceptance Rate

KMO Value	Level of Acceptance
≥ 0.9	Excellent
0.8 – 0.89	Good
0.7 – 0.79	Fair
0.6 – 0.69	Moderate
< 0.6	Inadequate

Meanwhile, the reliability test employed Cronbach's Alpha. Cronbach's Alpha was used to evaluate whether the research instrument could be considered reliable (Utami, Rasmanna, & Khairunnisa, 2023). The Cronbach's Alpha formula is as follows:

$$\alpha = \frac{N * \bar{c}}{\bar{v} + (N-1)*\bar{c}} \tag{3}$$

Where *N* is the number of data points, $\bar{c}$ is the average variance between items, and $\bar{v}$ is the overall average item variance.

2.2 Pre-processing Data

Data preprocessing is a crucial step in data mining analysis, aimed at cleaning, reformatting, and preparing data to ensure accuracy and readiness for subsequent analysis (Daniswara & Nuryana2, 2023). The data preprocessing process involves handling raw data obtained from surveys. The steps taken include checking data completeness, particularly addressing missing values. Next, outliers in the data were identified using the Z-Score method with a threshold of 3.0, where any value exceeding this threshold was considered an outlier. Outliers were examined for each numerical column. In this study, detected outliers were not addressed since their number was minimal and considered to have no significant impact on the final analysis results. The formula for calculating outliers using the Z-score is as follows:

$$Z = \frac{X-\mu}{\sigma} \tag{4}$$

Where X represents an individual data value, μ is the dataset mean, and σ is the dataset standard deviation.

Next, data normality was tested using the Shapiro-Wilk test, which indicated that all columns were not normally distributed based on p-values less than 0.05. The formula for the Shapiro-Wilk test is as follows:

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{5}$$

Where $x_{(i)}$ represents the sample data sorted from smallest to largest, x_i is the original data, $\bar{x}$ is the sample mean, a_i are coefficients computed based on the mean, variance, and covariance of a normal population, and n is the sample size.

Therefore, data normalization was performed using Min-Max Scaling to convert each variable's values into a range of 0 to 1. The Min-Max Scaling formula is as follows:

$$x' = \frac{x-x_{min}}{x_{max}-x_{min}} \tag{6}$$

Where x is the original data value, x_{min} is the minimum value in the dataset, and x_{max} is the maximum value in the dataset.

2.3 Descriptive Analysis

Descriptive analysis is conducted to identify patterns and the overall distribution of the data. This stage not only provides an initial overview of the variables related to e-commerce selection but also helps researchers understand the characteristics of the dataset used. In this process, researchers calculate basic statistics such as mean, median, mode, and standard deviation for each variable to provide detailed quantitative information. Additionally, data distribution visualization is performed using charts such as histograms, boxplots, or scatter plots to offer a clear visual representation of the analyzed data. Visualization serves as a significant supporting tool, helping students develop a deeper understanding of the studied concepts while reducing the risk of misinterpretation (Schoenherr, Strohmaier, & Schukajlow , 2024). By utilizing descriptive analysis techniques, researchers can gain valuable initial insights, which in turn can guide the subsequent analysis stages to ensure more accurate and reliable research results.

2.4 LGCM Analysis

The Latent Growth Curve Modeling (LGCM) analysis is a statistical technique used to understand the development of variable changes over time (Wang, et al., 2022). This analysis process involves several key stages that allow researchers to explore deeper into the growth patterns of variables such as price, quality, and loyalty in the context of e-commerce. First, researchers need to identify the growth variables, which consist of two main components: intercept and slope (Cheong, MacKinnon, & Khoo, 2023). The intercept in the latent growth model represents the initial value or baseline level of the measured variable, reflecting customer conditions at a specific point in time, while the slope describes the rate of change of the variable over time, indicating how quickly growth occurs and the differences in the rate of change between individuals (Wang & Fang, 2024). By understanding these two components, researchers can analyze the dynamics of changes occurring in variables related to e-commerce, providing deeper insights into how and why these variables fluctuate (Curran & Bauer, 2021). Essentially, LGCM uses the following linear model:

$$y_{it} = \eta_0 + \eta_1 t + \epsilon_{it} \tag{7}$$

Where, y_{it} is the outcome measurement for individual i at time t, η_0 is the latent intercept, η_1 is the latent slope, t is the time of measurement, and ϵ_{it} is the measurement error associated with individual i at time t.

After identifying the growth variables, the next step is constructing the measurement model. This model links each manifest variable, such as price perception measured at multiple time points, to latent variables, namely the intercept and. Each time point is represented by a manifest variable serving as an indicator of the growth factors (Chen & Zhang, 2022). The assumption in this model is that the observed variables reflect changes occurring in the latent variables (Grimm, Ram, & Estabrook, 2022). The next process is parameter estimation, where the intercept and slope are estimated to describe the initial condition and the rate of change of variables over time (Brandmaier, Lindenberger, & McCormick, 2024). This estimation is typically performed using the Maximum Likelihood Estimation (MLE) method, known for its ability to provide accurate and reliable estimates. Maximum Likelihood Estimation (MLE) is a statistical method for estimating model parameters by maximizing the likelihood that the observed data originate from the model. MLE selects parameter values that maximize the likelihood function, which measures how probable the observed data are given the model. MLE can be used to maximize the likelihood function in parameter estimation for both fixed and random effects (Harahap & Sutarman, 2023). MLE also exhibits asymptotic normality properties, where its distribution approaches a normal distribution as the sample size increases (İŞBİLEN, 2023). The general formula for MLE is:

$$L(\theta) = \prod_{i=1}^{n} f(x_i|\theta) \tag{8}$$

To simplify the process, the log-likelihood function is commonly used:

$$\log L(\theta) = \sum_{i=1}^{n} \log f(x_i|\theta) \tag{9}$$

Next, the parameter θ that maximizes the likelihood function is obtained by solving the equation:

$$\frac{\partial}{\partial\theta} \log L(\theta) = 0 \tag{10}$$

Where, $L(\theta)$ is the likelihood function, θ is the parameter to be estimated, $f(x_i|\theta)$ is the probability density function of data x_i dependent on parameter θ, n is the sample size, $log\ \ L(\theta)$ is the natural logarithm of the likelihood function, and $\frac{\partial}{\partial\theta} \log L(\theta)$ is the partial derivative of the log-likelihood function concerning parameter θ.

The next step is conducting a significance test. This stage aims to determine whether the slope differs significantly from zero, indicating variable changes over time (Martin, et al., 2024). The analysis also involves assessing the influence of external factors on the intercept and slope, known as LGCM with covariates (Wang, Zhang, & McArdle, 2020). The significance test is performed using p-values and z-values to evaluate the impact of external variables on growth dynamics. The z-value is used to determine the relative position of parameter estimates against the null hypothesis, while the p-value represents the probability of obtaining results as extreme as the observed ones if the null hypothesis is true. If $p < 0.05$, the result is considered statistically significant.

After the significance test, the next stage is model fit evaluation, which aims to assess how well the developed model aligns with the existing data (Nest, Passos, Candel , & Breukelen, 2020). Various indices, such as the Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI), are used to evaluate model fit.

The Root Mean Square Error of Approximation (RMSEA) assesses model fit while accounting for model complexity. RMSEA values range from 0 to 1, with lower values indicating better fit. According to Efrida et al., an RMSEA value below 0.05 indicates good fit, while values between 0.05 and 0.08 are still acceptable (Efrida, Hamidi, & Desweni, 2023). The formula for RMSEA is:

$$RMSEA = \sqrt{\frac{x^2}{df} . \frac{1}{n-1}} \tag{11}$$

Where, x^2 is the Chi-Square of the proposed model, df is the degrees of freedom, and n is the sample size.

The Comparative Fit Index (CFI) evaluates how well the proposed model explains the data compared to an independent model assumed to have poor fit. CFI values range from 0 to 1, with values close to 1 indicating good model fit. A CFI above 0.95 suggests very good fit, while values between 0.90 and 0.95 are still acceptable (Zulfikar, 2019). The formula for CFI is:

$$CFI = 1 - \frac{(x^2_{model} - df_{model})}{(x^2_{independence} - df_{independence})} \tag{12}$$

The Tucker-Lewis Index (TLI), also known as the Non-Normed Fit Index (NNFI), assesses model fit in structural equation modeling. TLI values range from 0 to 1, with values close to 1 indicating good fit. According to Halim et al., TLI considers model complexity and penalizes overly complex models, encouraging the selection of simpler yet effective models (Halim, Sari, & Nofranita, 2023). The formula for TLI is:

$$TLI = \frac{\left(\frac{x^2_{independence}}{df_{independence}}\right) - \left(\frac{x^2_{model}}{df_{model}}\right)}{\left(\frac{x^2_{independence}}{df_{independence}}\right) - 1} \tag{13}$$

Where, x^2_{model} is the Chi-Square value for the proposed model, df_{model} is its degrees of freedom, $x^2_{independence}$ is the Chi-Square value for the independent model, and $df_{independence}$ is its degrees of freedom.

The final step is visualizing the growth trajectory. By visualizing how each variable fluctuates over time, researchers can identify patterns and trends that might not be evident from numerical analysis alone. The generated graphs illustrate variable dynamics for the entire sample and specific subgroups. In the result interpretation stage, researchers analyze the intercept and slope components to understand initial conditions and variable changes over time. This interpretation is crucial for assessing the impact of external factors on growth, such as determining whether innovation contributes to changes in customer loyalty. Through this approach, researchers can gain a deeper understanding of the underlying dynamics influencing variable changes.

RESULTS AND DISCUSSION

1. Data Collection and Testing

Data collection was calculated using the Slovin formula as explained in equation (1), with a population of 212,881, representing the number of late adolescents in Surabaya, and a margin of error of 0.05. Based on the calculation, the minimum sample size obtained was 399 respondents. This indicates that data collected from at least 400 respondents is considered sufficient to represent the late adolescent population in Surabaya for this study. This sampling approach allows for valid and accurate generalization in line with the population's characteristics.

The sampling method used was simple random sampling, where each individual in the population had an equal opportunity to be selected. Data were collected through a structured questionnaire distributed via Google Form, which included indicators measuring key factors such as price, quality, loyalty, and innovation. Each main factor (except innovation) was represented by three itemized questions rated on a Likert scale, allowing the data to be processed in statistical models such as Latent Growth Curve Modeling (LGCM). This structured and representative approach ensures that the data are suitable for analysis and reflect real conditions within the target population.

Table 3. Cronbach's Alpha Value for Each Variable

Variable	**Value**
Price	0.78
Quality	0.77
Loyality	0.81

The reliability test results show that the variables Price (0.78), Quality (0.77), and Loyalty (0.81) have Cronbach's Alpha values that indicate adequate internal consistency. The Innovation variable could not be calculated because it consists of only one item. For validity testing, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was conducted and yielded a value of 0.89, which exceeds the commonly accepted threshold of 0.60. The KMO test evaluates the proportion of variance among variables that might be common variance (i.e., shared variance that is suitable for factor analysis). A KMO value close to 1.0 suggests that the patterns of correlations are relatively compact, and thus, factor analysis should yield distinct and reliable factors. Therefore, a KMO value of 0.89 in this study confirms that the data is highly appropriate for further factor analysis and supports the construct validity of the measurement instrument used.

2. Data Pre-processing

The data preprocessing stage includes handling missing values, outliers, normality tests, and normalization. The dataset consists of responses from 400 late adolescents in Surabaya, each responding to a structured questionnaire covering four key variables: Price, Quality, Loyalty, and Innovation. Each of the first three variables is measured using three items (e.g., Price1, Price2, Price3), while Innovation is measured with one item. These numeric responses, collected using a Likert scale from 1 to 10, form the basis of the analysis. During preprocessing, missing values are filled with the column mean, ensuring that no empty values remain. Outliers are identified using the Z-Score method with a threshold of 3.0, but are retained because their quantity is minimal and their influence is statistically insignificant. The Shapiro-Wilk normality test indicates that all variables do not follow a normal distribution (p-value < 0.05), prompting the use of Min-Max Scaling to normalize the data into a standard range of [0, 1]. This ensures consistency across features and prepares the dataset for robust modeling using Latent Growth Curve Modeling (LGCM).

3. Descriptive Analysis

Descriptive analysis shows that most variables have high average values, especially in the dimensions of loyalty and quality, with average values above 0.7 on a scale of [0, 1].

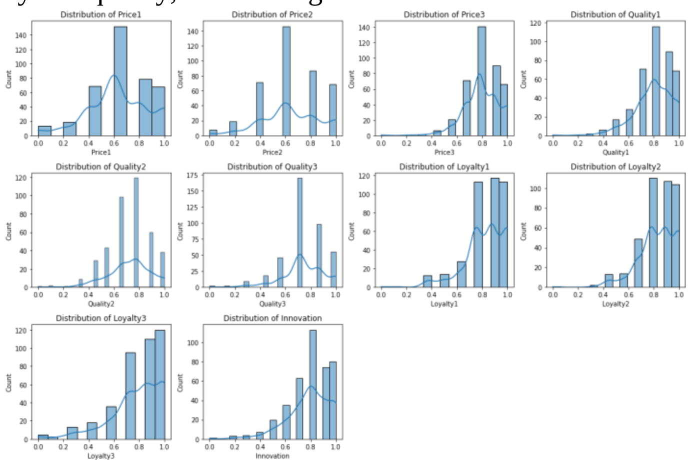

Figure 2. data distribution

The data distribution tends to be left-skewed (negatively skewed), indicating that the majority of respondents gave high ratings to these factors. Some variables, such as Price3, Loyalty1, and Innovation, have kurtosis values above 2, indicating a more peaked distribution. These results suggest that respondents tend to have consistent preferences for the measured factors. The distribution visualization supports these findings, with most variables showing a distribution pattern with a prominent peak in the high-value range. This reflects a uniform pattern of ratings among respondents.

4. Latent Growth Curve Modeling Analysis

4.1 Identification of Growth Variables

The results of the growth variable identification show that for the Price variable, the intercept value of 0.5302 indicates a relatively moderate initial value, with a slope of 0.0811, suggesting an average increase over time. The Quality variable has an intercept value of 0.8127, indicating a higher initial value, but the negative slope of -0.0285 suggests a decrease on average over time. For the Loyalty variable, the intercept value of 0.8508 indicates a very good initial value, but the negative slope of -0.0188 suggests a very small decline in loyalty over the observation period. Overall, these results provide an overview of the dynamics of the analyzed variables, with most showing a decrease or stability over time, except for Price, which is experiencing growth.

4.2 Modeling

The analysis results using the Measurement model in Latent Growth Curve Modeling

(LGCM) show that the applied model was successfully estimated with the normalized data. This model includes latent variables such as Price, Quality, and Loyalty, each represented by several observation items (Price1, Price2, Price3; Quality1, Quality2, Quality3; Loyalty1, Loyalty2, Loyalty3). Additionally, the model identifies the intercept and slope variables for each variable, representing the initial value and the rate of change of each variable over time. The influence of the Innovation variable on the intercept and slope for each variable is also incorporated into the model, indicating that Innovation has a relationship with changes in the initial value and growth rate of these variables. Furthermore, covariances between the intercept and slope for each variable, as well as between relevant error terms, were added to improve model fit. The model fitting process resulted in good convergence with an objective function value of 0.0937, indicating that the model adequately represents the relationships between variables in this study. Thus, the applied LGCM model provides good results regarding the dynamics of variable changes and the influence of Innovation on its growth.

4.3 Parameter Estimation

The parameter estimation results from the Measurement model in Latent Growth Curve Modeling (LGCM) provide insights into the relationships between the analyzed variables. The parameter estimates show that the Innovation variable has a significant influence on the intercept and slope for several variables.

	lval	op	rval	Estimate	Std. Err	z-value	p-value
0	Intercept_Harga	~	Inovasi	0.504364	0.066557	7.577945	0.0
1	Slope_Harga	~	Inovasi	-0.133106	0.029361	-4.533476	0.000006
2	Intercept_Kualitas	~	Inovasi	0.367437	0.039473	9.30867	0.0
3	Slope_Kualitas	~	Inovasi	0.002025	0.023569	0.085903	0.931543
4	Intercept_Loyalitas	~	Inovasi	0.391711	0.042462	9.224885	0.0
...	...	...	...	...	...	...	...
59	Harga3	~~	Harga3	0.007175	0.002495	2.875513	0.004034
60	Kualitas3	~~	Loyalitas3	-0.001342	0.00119	-1.127422	0.259564
61	Kualitas3	~~	Kualitas3	0.009383	0.002229	4.209039	0.000026
62	Loyalitas2	~~	Loyalitas2	0.005215	0.000951	5.485755	0.0
63	Loyalitas3	~~	Loyalitas3	0.025185	0.002319	10.861728	0.0

Figure 3. Parameter Estimation

For example, the effect of Innovation on the intercept of Price is positive with an estimate of 0.504364 (p-value = 0.0), indicating that Innovation is associated with a higher initial value for Price. On the other hand, the effect of Innovation on the slope of Price is negative with an estimate of -0.133106 (p-value = 0.000006), suggesting a decrease in the growth rate of Price over time. In the case of Quality, Innovation significantly influences the intercept (estimate = 0.367437, p-value = 0.0), while its effect on the slope is not significant (p-value = 0.931543), implying that the rate of change in Quality is unaffected by Innovation. A similar pattern appears in the Loyalty variable, where Innovation significantly affects the intercept (estimate = 0.391711, p-value = 0.0) and also has a significant positive effect on the slope. Covariance estimates between error terms for several items, such as between Price3 and itself (0.007175, p-value = 0.004034) and Quality3 with Quality3 (0.009383, p-value = 0.000026), further support the presence of significant interrelationships. These parameter estimation results highlight the strong role of Innovation in influencing the initial state (intercept) of all variables, even though its impact on growth trends (slope) varies.

Furthermore, the reliability and validity of these parameter estimates are strongly supported by the large sample size used in this study, consisting of 400 respondents. The relationship between parameter estimation and the number of respondents is crucial larger sample sizes provide more accurate, stable, and generalizable results. In LGCM, having sufficient data enhances the model's statistical power, reduces the standard errors of estimates, and ensures that the model can handle complex structures involving latent variables. With this large sample, the findings from the LGCM analysis in this study can be considered robust and representative of the broader late adolescent population in Surabaya.

4.4 Significance Test

The significance test for slope coefficients and the effect of a covariate like Innovation on intercepts and slopes in Latent Growth Curve Modeling (LGCM) typically uses the z-test formula, which is based on standard normal distribution. The formula is:

$$z = \frac{\hat{\beta}}{SE(\hat{\beta})} \quad (14)$$

Where $\hat{\beta}$ is the estimated parameter (e.g., slope or regression coefficient) and $SE(\hat{\beta})$ is the standard error of the estimate. Once the z-value is obtained, the p-value is computed to determine statistical significance. The two-tailed p-value is calculated using the cumulative distribution function (CDF) of the standard normal distribution:

$$p - value = 2 \times (1 - \Phi(| z |)) \quad (15)$$

Where $\Phi(| z |)$ is the CDF of the standard normal distribution at the absolute value of z.

The significance test results for the slope and the effect of the Innovation covariate on the intercept and slope show the dynamics of the analyzed variables. For the Price variable, the slope estimate of -0.133106 with a very small p-value (0.000006) indicates that the rate of change in Price significantly decreases over time. Conversely, for the Quality variable, the slope estimate of 0.002025 with a very high p-value (0.931543) shows that there is no significant effect of time on Quality, meaning the rate of change in Quality is not significant. The Loyalty variable also shows a small change in the slope, with a value of 0.025185 and a p-value of 0.0, indicating a significant growth rate in Loyalty.

Additionally, the impact of the Innovation covariate on the intercept and slope shows significant effects. Estimates for Intercept_Price, Intercept_Quality, and Intercept_Loyalty all show significant positive estimates with very small p-values (0.0), meaning that Innovation has a positive effect on the initial value (intercept) for all three variables. The higher intercept values reflect the impact of Innovation in increasing the initial values for Price, Quality, and Loyalty. These results indicate that Innovation affects both the initial values and the rate of change of several variables, with a more significant impact on the intercept than on the slope. Overall, these results suggest that Innovation plays an important role in influencing the development of the values of the studied variables.

4.5 Model Evaluation

The model fit evaluation results indicate values that support a good model fit. Below are the model evaluation results:

Table 4. Model Evaluation

Index	Value
RMSEA	0.0730
CFI	0.9844
TLI	0.9402

Based on Table 4, the RMSEA value of 0.0730 indicates that the model fits the data well, as an RMSEA value below 0.08 signifies an adequate model. Additionally, the CFI value of 0.9844 and the TLI value of 0.9402 indicate that the model fits the data very well. CFI and TLI values greater than 0.90 are often considered to indicate a good fit with the data. Overall, these results show that the applied model fits the data very well, supporting the model's validity in representing the relationships between the analyzed variables.

4.6 Visualization

The growth trajectory visualization is used to analyze the dynamics of changes in price, quality, and customer loyalty to e-commerce over time. This visualization aims to provide an overview of the development patterns of each variable, allowing for the identification of trends or significant changes that occur during the observation period.

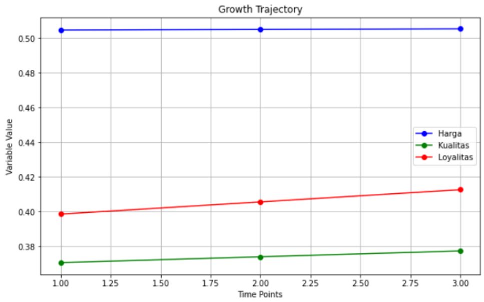

Figure 4. Growth Trajectory

Figure 4 shows the growth trajectory visualization for the variables of price, quality, and customer loyalty to e-commerce. The graph reveals distinct patterns for each variable over time. The price variable maintains relatively constant values across time points, as indicated by the horizontal line. This suggests that perceptions of price did not undergo significant changes during the observed period.

In contrast, the quality and loyalty variables exhibit increasing values over time, as seen from the lines with positive slopes. The quality trajectory shows a slower growth rate compared to loyalty, indicating that efforts to improve service quality on e-commerce platforms take longer to significantly impact customer perceptions. However, the faster increase in customer loyalty may suggest that users are more responsive to certain improvements or innovations on the platform.

These results provide important implications for e-commerce managers to focus strategies on enhancing service quality and customer loyalty, as both demonstrate more dynamic growth potential compared to the price variable. Consistent improvements in quality can support more significant long-term growth in loyalty, strengthening the relationship between users and the platform. This study provides valuable insights into the dynamics of key variables influencing customer loyalty to e-commerce. The growth trajectory visualization also emphasizes the need for a data-driven approach in strategic decision-making within the e-commerce industry.

4.7 Interpretation of Results

The results of the Latent Growth Curve Modeling (LGCM) provide insights into the changes in perceptions of Price, Quality, and Loyalty over time, as well as the impact of the covariate Innovation on these three variables. For the Price variable, the intercept value of 0.504 indicates that the initial perception of price is relatively high, while the very small slope (0.000) suggests that there is no significant change in price perception over time. This indicates that preferences regarding price remain relatively stable throughout the observation period.

For the Quality variable, the intercept value of 0.367 reflects a positive initial perception of quality, and the slope of 0.003 indicates a slight increase in the perception of quality over time, although this change is very small and practically insignificant. Meanwhile, for Loyalty, the intercept value of 0.392 reflects a fairly high initial level of loyalty. The slope of 0.007 shows a slight increase in customer loyalty, although this change is also small.

The impact of the covariate Innovation on all three variables shows a significant effect on the intercept of each variable. The intercept values for Price (0.504), Quality (0.367), and Loyalty (0.392) all show a positive influence from Innovation. This indicates that innovation contributes to improving the initial perceptions of price, quality, and customer loyalty, suggesting that innovation can play an important role in influencing consumer preferences for these three aspects.

The final results of this study show that price and quality are the two main factors influencing the decision of adolescents in choosing e-commerce, although changes in perceptions of both are relatively small over time. Customer loyalty tends to remain stable but slightly increases, reflecting the importance of trust and positive experiences. Innovation plays a significant role in influencing perceptions of price, quality, and loyalty by introducing new features or attractive offers. Overall, price, quality, and loyalty are key factors in e-commerce selection, with innovation strengthening this relationship.

CONCLUSION

The Latent Growth Curve Modeling (LGCM) results indicate that the Price variable starts at a moderate level (intercept = 0.5302) and shows a positive growth trend (slope = 0.0811), whereas Quality (intercept = 0.8127, slope = -0.0285) and Loyalty (intercept = 0.8508, slope = -0.0188) exhibit slight declines over time. The model demonstrates excellent fit indices (RMSEA = 0.0730, CFI = 0.9844, TLI = 0.9402), confirming the robustness of the findings. Importantly, the parameter estimates reveal that Innovation significantly influences the initial levels (intercepts) of all variables, although its impact on their growth rates (slopes) varies. Specifically, innovation positively affects the initial perception of Price (0.504364, $p < 0.001$) but negatively influences its growth rate (-0.133106, $p < 0.001$). Innovation also enhances the intercepts for Quality and Loyalty, with the strongest and most consistent effect observed on Loyalty.

These results are grounded in the responses collected from a diverse group of respondents, whose perceptions and experiences shaped the measurement of Price, Quality, Innovation, and Loyalty over time. The variability in intercepts and slopes reflects how respondent characteristics and changing attitudes impact these constructs longitudinally, highlighting the importance of respondent input in understanding the dynamics of e-commerce factors. The trajectory visualization shows that the Price variable remains stable over time, while Quality and Loyalty exhibit slow increases. The growth of Loyalty is more significant compared to Quality, reflecting a quicker customer response to innovations or improvements on the e-commerce platform. These results emphasize the importance of innovation in improving customers' initial perceptions of price, service quality, and loyalty, while also providing strategic implications for e-commerce managers to prioritize consistent service quality improvements to support long-term customer loyalty.

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