

Partial Least Square Structural Equation Modeling (SEM-PLS) Analysis for Modeling the Purchase of Swallow's Nest Drinks

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ABSTRACT

Consumer preferences are an individual's likes or dislikes regarding the products they consume. Consumer preferences are also the values that consumers consider when making a choice. Considerations in selecting a product type usually occur more frequently when there is sufficient or excess supply of materials. Various factors can influence a person's considerations regarding the products they choose and like. Purchase intent significantly influences the quantity and type of products to be purchased. Other influential factors include purchasing power, consumer perception, and subjective evaluation of a product. To address this issue, this study will develop an empirical research model using five research variables: purchase intent, purchasing power, consumer perception, and subjective evaluation. Among these five variables, the study will identify which ones require improvement. This study uses secondary company data from a questionnaire distributed to 42 respondents, followed by data analysis using SEM-PLS. The results of the study show that the SEM PLS consumer preference model has an AIC value for purchase intention of -31.511. A small AIC value indicates that the model is effective in identifying consumer preferences through the variables of purchase intention, purchasing power, consumer perception, and subjective evaluation. The results of the study show that purchasing power, consumer perception, and subjective evaluation have a significant influence on purchase intention. The purchasing power variable increases purchase intention by 0.543, the consumer perception variable by 0.349, and the subjective evaluation variable by 0.214. Recommendations for improvement are provided to Company X at the end of the study to further enhance the variables that contribute significantly.

Keywords: AIC, Consumer Preferences, PLS, SEM, SEM-PLS

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1. Introduction

The swiftlet nest is the dried saliva of the swiftlet bird, which has numerous health benefits for the body. Swiftlet nests are commonly referred to as a premium delicacy due to their high price. Despite their high cost, swiftlet nests contain nutrients that are beneficial for health [1]. This bird's nest delicacy is also deeply ingrained in people's minds, with many believing it originates from China. However, bird's nests are actually a food that originates from and can be found in Southeast Asia, including Indonesia [2].

Indonesia is one of the countries that supplies the most bird's nests for export to several countries, with the largest exports going to Hong Kong and China. According to data from the Ministry of Trade of the Republic of Indonesia, when ranked

among the world's major suppliers of swallow nests, Indonesia tops the list, supplying 38.57% of the global demand for swallow nests, followed by Singapore (28%), Hong Kong (4.69%), and Malaysia (4.64%). Exports of bird's nests have also continued to increase annually.

The positive growth of this industry is also attributed to the increasing awareness among the public about the benefits of bird's nests, including boosting the immune system, maintaining youthful skin, and improving metabolic processes. This also shows that market interest in swallow nests in Indonesia is increasing and giving rise to a new trend related to health drinks and foods, commonly referred to as functional foods [3].

This trend is also in line with the changes brought about by the Covid-19 pandemic, which has forced people to maintain and

boost their immune systems by consuming healthy foods and beverages. As a booster for the immune system, functional foods are one of the best sources of nutrition for the body. Although consumption of functional foods has increased alongside growing public awareness of the importance of adopting a healthy lifestyle during the pandemic, the market for functional foods remains very small among millennials compared to the market for conventional foods and beverages [4]. The marketing of bird's nest beverages is closely tied to purchase intensity, which can serve as an early indicator of consumer purchasing decisions. Purchase intent can be influenced by purchasing power, consumer perception, and subjective evaluation [5,6,7]. Therefore, to increase sales of bird's nest drinks, Company X is interested in evaluating purchase intent, purchasing power, consumer perception, and subjective evaluation of the product using multivariate analysis with the SEM-PLS method.

Multivariate analysis is a statistical method used to analyze data on more than one variable (multivariate) simultaneously and produce comprehensive interpretations. Multivariate analysis is classified into two types based on the pattern of relationships

between variables: dependency analysis and interdependence analysis. Dependency analysis aims to determine the causal relationship between variables, as in [8,9,10]. Meanwhile, interdependence analysis connects variables without involving causal relationships, only covering exploratory and descriptive analysis, as in [11,12].

2. Method Details

2.1. Data Collection

The data used is demographic data on respondents, including their age, consumer perceptions, purchasing power, purchase intentions, and subjective evaluations from focus group discussions (FGDs), which are part of a series of beverage product research. Data collection was conducted directly using questionnaires from June 5 to 8, 2023.

2.2. Research Variables

The research variables used can be seen in Table 1.

Table 1. Research Variables

Variable	Indicator	Category
Age	-	1: 20–25 years old 2: 26–30 years old 3: 31–35 years old 4: 36–40 years old 5: > 40 years old
Consumer Perception	PS1: Beliefs regarding health PS2: Beliefs regarding beauty PS3: Beliefs regarding mental health PS4: Willingness to consume daily PS5: Beliefs regarding consumption of products without halal labeling PS6: Beliefs regarding consumption of products without official labeling PS7: Attitude of prioritizing taste over benefits PS8: Consideration of product packaging design PS9: Belief in the use of authentic ingredients PS10: Belief in consuming products without nutritional labels PS11: Price suitability with portion size PS12: Price suitability with flavor variations	1: Strongly disagree 2: Disagree 3: Agree 4: Strongly agree
Subjective Evaluation	Aroma Thickness Complexity of flavor Sweetness Texture Color	1: Strongly disagree 2: Disagree 3: Agree 4: Strongly agree
Purchasing Power	DB1: Purchasing products based on needs DB2: Researching information before purchasing DB3: Purchasing based on price-quality ratio DB4: Purchasing based on recommendations from others DB5: Comparing product quality DB6: Completeness of information DB7: Availability on e-commerce platforms DB8: Consideration of materials used DB9: Consideration of nutritional content	1: Strongly disagree 2: Disagree 3: Agree 4: Strongly agree

Variable	Indicator	Category
	DB10: Consideration of listed ingredients	1: Strongly disagree 2: Disagree 3: Agree 4: Strongly agree
	DB11: Prioritizing ingredients over price	
	DB12: Purchasing health products without considering price	
	DB13: Prioritizing price over ingredients	
	DB14: Interest in attractive packaging despite high price	
	DB15: Interest in inexpensive products with attractive packaging over expensive ones	
Purchase Intensity	DB16: Purchasing products due to cute and attractive packaging	
	IP1: Interest in terms of packaging	
	IP2: Interest in terms of product quality	
	IP3: Interest in terms of price	

Consumer perception variables are measured using 12 indicators, purchasing power variables are measured using 16 indicators, purchase intensity variables are measured using 5 indicators, and subjective evaluation variables are measured using 6 indicators.

2.3. Structural Equation Modeling Partial Least Square (SEM-PLS)

Structural Equation Modeling Partial Least Square (SEM-PLS) is a statistical analysis method used to test the relationship between latent variables measured through observable indicators. SEM-PLS is one of the techniques in Structural Equation Modeling (SEM) that is particularly useful in research with high complexity, especially when the sample size is relatively small and the data is not normally distributed. SEM-PLS is a variance-based approach developed by Herman Wold in the 1970s.

This method aims to maximize the variance explained by the model by optimizing the relationship between latent variables and their indicators, as well as the relationships between latent variables themselves [15]. SEM-PLS consists of two main models: the measurement model (outer model), which explains the relationship between latent variables and their indicators, and the structural model (inner model), which explains the relationships among latent variables within the model. In the measurement model, there are two types of measurement models: reflective, where the indicators are manifestations of the latent variables, and formative, where the latent variables are the result of a combination of indicators.

In the reflective model, the loading factor value of each indicator is used to measure how well the indicator reflects the latent variable. A loading factor greater than 0.5 is considered acceptable and indicates that the indicator has a significant contribution to the latent variable. In addition, the structural model can test the causal hypotheses proposed in the study [15]. To ensure the quality of the measurement model, several steps

can be taken, such as convergent validity, discriminant validity, and composite reliability [16,17].

2.4. Prediction-Oriented Segmentation Partial Least Square (POS-PLS)

Prediction-Oriented Segmentation Partial Least Square (POS-PLS) is an analysis technique used for data segmentation in the Structural Equation Modeling Partial Least Square (SEM-PLS) model. This method aims to identify heterogeneous segments in the data that can improve the accuracy of model predictions and understanding of the relationships between latent variables in various subpopulations. POS-PLS is an extension of the PLS-SEM technique that emphasizes prediction-based segmentation. This technique helps researchers identify and understand subgroups in the data that may have different patterns of relationships between latent variables [18].

POS-PLS integrates segmentation with SEM-PLS analysis through several stages, namely segment identification, segment evaluation, and SEM-PLS model analysis in each segment. Segment identification uses a specific algorithm to divide data into several segments based on prediction criteria. Segment evaluation assesses the quality of segmentation by measuring the accuracy of predictions in each segment. Meanwhile, SEM-PLS model analysis within each segment can be conducted after the segments have been identified. SEM-PLS analysis is performed separately within each segment to understand the relationships between latent variables. These relationships will serve as analytical results that can be beneficial for research.

2.5. Multiple Correspondence Analysis

Multiple Correspondence Analysis (MCA) is a statistical technique used to analyze categorical data. This technique extends simple correspondence analysis (Correspondence Analysis, CA), which can only be used for two-way contingency tables, allowing MCA to be applied to multidimensional contingency tables. MCA is an exploratory method useful for

identifying patterns in categorical data by mapping the data into a low-dimensional space. Thus, MCA aids in visualizing relationships between categories across various variables. MCA can generate factor maps that facilitate the interpretation of relationships between categories [19]. MCA's ability to handle complex data makes it suitable for data with many predictor variables and categories [20]. MCA also does not require data to meet certain distribution assumptions, making it more flexible in its application [21,22].

3. Results and Discussion

3.1. Descriptive Analysis

Descriptive analysis is used to examine the characteristics of the data used in the study. The results of the descriptive analysis are shown in Figure 1 below.



Figure 1. Results of Descriptive Analysis

Based on Figure 1 (a), it can be seen that the respondents mostly answered option 3 with 51.39%, while options 1, 2, and 4 were answered with 13.10%, 25.40%, and 10.12%, respectively. Based on Figure 1 (b), it can be seen that the majority of respondents chose answer option 3 at 46.28%, while answer options 1, 2, and 4 were chosen at 4.32%, 25.15%, and 24.26%, respectively. Based on Figure 1 (c), it can be seen that the respondents mostly answered option 3 with 58.10%, while options 1, 2, and 4 were answered with 9.52%, 19.05%, and 13.33%, respectively. Based on Figure 1 (d), it can be seen that the majority of respondents answered option 4 at 40.08%, while options 1, 2, 3, and 5 were chosen at 0.40%, 10.32%, 34.52%, and 14%, respectively.

3.2. Multiple Correspondence Analysis

The results of the multiple correspondence analysis are presented visually through the plot shown in Figure 2.

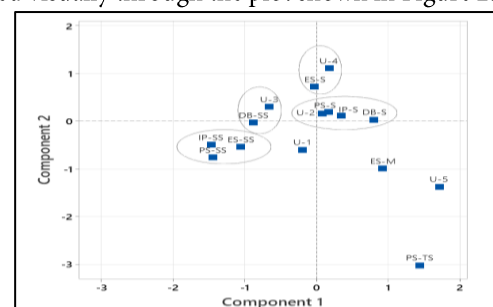


Figure 2. Correspondence Analysis Biplot

Figure 2 shows that consumers who chose the answer “strongly agree” in consumer perception tend to strongly agree with purchase intensification and strongly like subjective evaluation. Consumers in age category 3 (31–35 years old) tend to have very high purchasing power by answering “strongly agree” in the purchasing power section. Consumers in age category 4 (36–40 years old) tend to like subjective evaluation. Consumers in age category 2 (26–30 years old) tend to choose the answer “agree” in consumer perception, as well as have high purchase intensity and purchasing power, by choosing “agree” in the purchase intensity and purchasing power sections.

3.3. Validity and Reliability

Validity testing is used to see whether the indicators for each variable are valid and can be used in the model. The results of the validity testing are presented in Table 2.

Table 2. Validity Test Results

Variable	r test	r table	Description
PS1	0.343	0.3044	Valid
PS2	0.335	0.3044	Valid
PS3	-0.036	0.3044	Not Valid
PS4	0.362	0.3044	Valid
PS5	0.254	0.3044	Not Valid
PS6	0.47	0.3044	Valid
PS7	0.405	0.3044	Valid
PS8	-0.066	0.3044	Not Valid
PS9	0.453	0.3044	Valid
PS10	0.157	0.3044	Not Valid
PS11	0.113	0.3044	Not Valid
PS12	0.282	0.3044	Not Valid
DB1	0.198	0.3044	Not Valid
DB2	0.405	0.3044	Valid
DB3	0.212	0.3044	Not Valid
DB4	0.267	0.3044	Not Valid
DB5	0.497	0.3044	Valid
DB6	0.565	0.3044	Valid
DB7	0.568	0.3044	Valid
DB8	-0.013	0.3044	Not Valid
DB9	0.139	0.3044	Not Valid
DB10	0.215	0.3044	Not Valid

Variable	r test	r table	Description
DB11	0.222	0.3044	Not Valid
DB12	0.168	0.3044	Not Valid
DB13	0.126	0.3044	Not Valid
DB14	0.194	0.3044	Not Valid
DB15	0.256	0.3044	Not Valid
DB16	0.178	0.3044	Not Valid
IP1	0.328	0.3044	Valid
IP2	0.46	0.3044	Valid
IP3	0.612	0.3044	Valid
IP4	0.222	0.3044	Not Valid
IP5	0.185	0.3044	Not Valid
Aroma	0.378	0.3044	Valid
Manis	0.426	0.3044	Valid
Tekstur	0.613	0.3044	Valid
KR	0.604	0.3044	Valid
Kekentalan	0.588	0.3044	Valid
Warna	0.581	0.3044	Valid

Based on the validity test results, there were several invalid indicators. Therefore, these invalid indicators were eliminated. The reliability test results can be seen based on the Cronbach's alpha value. The Cronbach's alpha results are provided in Table 3.

Table 3. Reliability Test Results

Cronbach's Alpha	N
0.838	19

Based on the reliability test results, Cronbach's alpha value of 0.838 was obtained. Cronbach's alpha result is greater than 0.7, making it reliable.

3.4. Modelling

The main purpose of conducting SEM analysis is to investigate the factors that influence the intention to purchase swallow's nest drinks. Therefore, the initial stage of modeling is to establish the relationships between variables. This study aims to investigate the factors that influence consumer purchase intentions. The SEM PLS path diagram used can be seen in Figure 3.

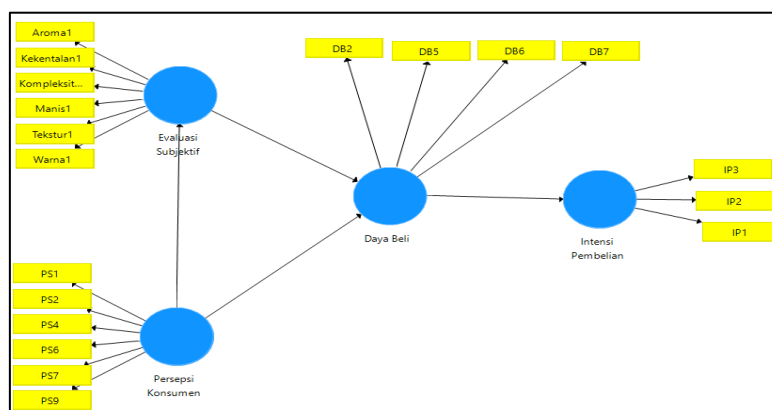


Figure 3. SEM-PLS Path Diagram

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Each variable used in the modeling is formed by several indicators (latent variables) that can be seen in Figure 3. Each variable has a factor loading that indicates the strength of the relationship between the latent variables and the variables that compose them. The largest factor loading is shown by the complexity of taste in subjective evaluation, indicating that the more complex the taste of the sarang wallet drink, the higher the subjective value given to the drink.

Then, the highest loading factor in the purchase intensity variable is found in the latent variables IP 2 and IP3, which indicate consumer confidence in product quality and price. This shows that it is important for companies to maintain product quality and affordable prices. Furthermore, in the purchasing power variable, attention should be paid to product quality (DB5) because it is the latent variable most closely related to purchasing power. Finally, consumer perception is most influenced by the belief that the product has an effect on beauty, as indicated by the highest loading factor on PS2. The complete loading factor values can be seen in Table 4.

Table 4. Outer Model Loading Factors

Route	Loading Factor
DB2 → Purchasing Power	0,568
DB5 → Purchasing Power	0,792
DB6 → Purchasing Power	0,693
DB7 → Purchasing Power	0,677
IP1 → Purchase Intention	0,638
IP2 → Purchase Intention	0,844
IP3 → Purchase Intention	0,820
PS1 → Consumer Perception	0,689
PS2 → Consumer Perception	0,728
PS4 → Consumer Perception	0,477
PS6 → Consumer Perception	0,458
PS7 → Consumer Perception	0,291
PS9 → Consumer Perception	0,648
Aroma → Subjective Evaluation	0,577
Viscosity → Subjective Evaluation	0,762
Flavor Complexity1 → Subjective Evaluation	0,865
Sweetness → Subjective Evaluation	0,777
Texture → Subjective Evaluation	0,687
Color → Subjective Evaluation	0,778

Based on the structural model that has been formed, the relationships between variables that were tested were consumer perceptions of purchasing power, consumer perceptions of subjective evaluation, consumer perceptions of purchasing power, subjective evaluation with purchasing power, and purchasing power with purchase intention. Before modeling and significance testing, latent variables with factor loadings less

than 0.5 were removed because they were deemed unsuitable for inclusion in the model, resulting in the removal of indicators PS4, PS6, and PS7. Based on the remaining latent variables, the significance test values with test statistics can be seen in Table 5.

Table 5. Direct Effect

Route	Coefficient	T-statistic	P-value
Purchasing Power → Purchase Intention	0,543	3,604	0,000
Subjective Evaluation → Purchasing Power	0,394	2,485	0,013
Consumer Perception → Purchasing Power	0,494	5,268	0,000
Consumer Perception → Subjective Evaluation	0,378	3,283	0,001

Subjective consumer evaluations of beverages have a significant influence on consumer purchasing power, and these evaluations are also influenced by consumers' perceptions of the swallow's nest beverage products offered. In addition, consumer perceptions are also a significant factor influencing purchasing power. Therefore, consumer perceptions have an influence on purchasing power, both directly and indirectly. Furthermore, higher purchasing power also has an impact on increasing purchase intensity. Therefore, to increase purchase intensity, it is necessary to enhance purchasing power, which can also be achieved by improving consumers' subjective evaluations and perceptions of the product. This can be seen in Table 2. Additionally, the overall indirect effects of the model can be observed in Table 6.

Table 6. Indirect Effect

Route	Coefficient	T-statistic	P-value
Subjective Evaluation → Purchase Intention	0,214	2,857	0,004
Consumer Perception → Purchasing Power	0,149	1,942	0,053
Consumer Perception → Purchase Intention	0,349	3,319	0,001

Each SEM PLS model that was formed can be expressed in terms of the AIC values for the direct effects on purchase intention, purchasing power, and subjective evaluation, which were -11.827, -31.511, and -4.651, respectively.

3.5. Clustering PLS-POS

PLS-POS is used to segment consumers based on the relationship between structures. In this case, consumers are grouped into three segments with segment membership 1, 2, and 3 totaling 11, 17, and 14, respectively. Each segment has distinct characteristics. The first group consists of consumers whose finances still depend on others, with the highest income

being less than 1 million. The second segment comprises consumers who have their own income but still depend on others, with salaries ranging from 1 to 4 million. The final segment consists of independent consumers with relatively high incomes. In addition to being analyzed through consumer demographics, PLS-POS can provide information on the differences in path coefficients generated by each segment. This can be seen in Table 7.

Table 7. Path Coefficients (segments)

Route	Seg 1	Seg 2	Seg 3
Purchasing Power → Purchase Intention	0,835	-0,836	0,947
Subjective Evaluation → Purchasing Power	0,402	0,987	0,134
Consumer Perception → Purchasing Power	0,587	0,461	0,859
Consumer Perception → Subjective Evaluation	0,624	-0,722	0,640

Based on the PLS-POS results, it can be seen that segment 1 will tend to have a higher purchase intention compared to segment 3 when purchasing power increases, unlike segment 2, which actually experiences a decrease in purchase intention as purchasing power increases. In addition, in segment 2, consumer perceptions also tend to have a negative influence on subjective evaluation, with the greatest influence compared to other segments.

However, for segment 2, subjective evaluation is the variable that most directly influences purchasing power. When viewed from the perspective of the influence of perception on purchasing power, segment 3 has the greatest influence on purchasing power through consumer perception. Therefore, for segment 1, purchasing power needs to be increased through improving consumer perception, subjective evaluation, or other methods, so that purchase intent can be increased. Furthermore, for segment 2, it is crucial to enhance subjective evaluation and increase product offerings so that when purchasing power increases, consumers are more inclined to purchase bird's nest beverage products. Meanwhile, for segment 3, enhancing purchasing power and consumer perception should be the primary focus to increase purchase intent.

Table 8. Outer Model Loading Factors

Route	Loading Factor		
	Seg 1	Seg 2	Seg 3
DB2 → Purchasing Power	0,501	-0,350	0,631
DB5 → Purchasing Power	0,676	0,122	0,901
DB6 → Purchasing Power	0,660	-0,648	0,876
DB7 → Purchasing Power	0,907	0,892	0,682
IP1 → Purchase Intention	0,614	0,356	0,913
IP2 → Purchase Intention	0,883	0,977	0,869
IP3 → Purchase Intention	0,809	-0,059	0,861
PS1 → Consumer Perception	0,826	0,849	0,172
PS2 → Consumer Perception	0,936	0,919	0,075

Route	Loading Factor		
	Seg 1	Seg 2	Seg 3
PS9 → Consumer Perception	0,848	-0,788	0,979
Aroma → Subjective Evaluation	0,472	0,705	0,303
Viscosity → Subjective Evaluation	0,843	0,366	0,913
Flavor Complexity → Subjective Evaluation	0,913	0,916	0,655
Sweetness → Subjective Evaluation	0,769	0,909	0,786
Texture → Subjective Evaluation	0,605	0,674	0,647
Color → Subjective Evaluation	0,692	0,841	0,616

Therefore, for the next marketing step, the Company must continue to improve product quality and highlight the benefits of the swallow's nest drink products offered. Furthermore, for segments 1 and 2, it is important for the Company to introduce the effectiveness of consuming swallow's nest products for beauty. In addition, to increase purchase intent in segment 2, certain offers can be made, such as discounts that can reduce the price of the product.

Meanwhile, in segment 3, it is important to introduce the product quality and effectiveness on feelings in more detail. Overall, consumers in segment 2 tend to have higher considerations for purchasing products, so a more in-depth approach is needed to increase purchases from consumers in this segment. The POS-PLS model that was formed had good results, as seen from the relatively large R^2 value shown in Table 9.

Table 9. R^2 values for each model.

Endogenous Variables	Average	Seg 1	Seg 2	Seg 3
Purchasing Power	0,704	0,939	0,479	0,791
Subjective Evaluation	0,532	0,188	0,498	0,845
Purchase Intention	0,761	0,700	0,689	0,897

Based on Table 10, the R^2 value for the endogenous variable of purchase intensity obtained the highest average of 0.761 or 76.1% compared to other variables.

4. Conclusion

Consumers aged 31–35 tend to have very high purchasing power, consumers aged 36–40 tend to prefer subjective product evaluations, while consumers aged 26–30 tend to have high perceptions, purchase intensity, and purchasing power. Consumer preferences have an AIC value of -31.511. A small AIC value indicates that the model is effective in assessing consumer preferences through the variables of purchase intention, purchasing power, consumer perception, and subjective evaluation. The research findings reveal that purchasing power, consumer perception, and subjective evaluation have a significant influence on purchase intention.

The purchasing power variable increases purchase intention by 0.294, the consumer perception variable by 0.462, and the subjective evaluation variable by 0.703.

Author Contributions Statement

Author 1: Conceptualization, Methodology

Author 2: Formal analysis, or investigation

Author 3: Preparation of the original draft or writing of the review and editing

Conflict of Interest Statement

- ☒ The authors declare that they have no competing financial interests or known personal relationships that could be considered to influence the work reported in this article.
- ☐ The authors declare the following financial/personal relationships that may be considered competing interests.

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