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ASSESSMENT OF MARKET SHARE AND BRAND PREFERENCE WITH MARKOV CHAIN AND FACTOR ANALYSIS APPROACH IN EAST JAVA

SRI RAHAYU[1*], OTTO FAJARIANTO[2], RIFDA FITRIANTY[3]

[1,3]Mahardhika School of Economic, Surabaya, Indonesia
[2]Faculty of Education, Universitas Negeri Malang, Malang, Indonesia

*Corresponding Author: rahayu.mahardhika@gmail.com

Abstract: Competition in the consumer product business is very tight hence, marketing strategies are needed to maximise product marketing. In the context of East Java, Indonesia, marketing of detergent products is complicated because there are many competing companies, and the factors concerning loyal consumers still need to be discovered. The present research aims to determine the right marketing strategy for each detergent brand by knowing consumer reactions and responses to the marketing strategies that companies implement. This research determines consumers' perceptions of certain detergent products which influence their purchasing behaviour and awareness of various risks of the products that they consume. Weighted data on Markov Chain is collected by utilising survey questionnaires, and the current behaviour of consumers is analysed to predict their behaviour regarding changes in detergent product selection through probabilistic information that can be used to assist decision-making. By using the Markov chain method, it is found that market share projections for the detergent products under study can be carried out. The factor that has the potential to cause consumers of certain detergent products to switch to other detergent products is the lack of fulfilment of product variations, and types. This research contributes to obtaining appropriate indicators and attributes to increase consumer perceptions of a product as part of a superior marketing strategy.

Keywords: Marketing strategy, Branding, Markov Chain, Consumer behaviour, Customer loyalty

1. Introduction

With rapid technological advances in the era of Industry 4.0, competition in running a business is increasingly high and intensive. With these advances, new products emerge that compete on quality, price, promotions, and other superior attributes. Hence, companies need the right marketing strategy to be able to compete to meet market demand (Revathy et. al, 2021). Several factors can influence market demand, including product quality, brand, packaging, price, and aroma. Elements outside the product include product distribution, market environment, and marketing strategy, and there are still many considerations that must be taken into account when marketing a product (Lakshmi & Jyothi, 2020; Isaac & Saha, 2021). Among the factors, brand switching according to the Markov chain method can be applied although it is often a dilemma in the world of commerce to carry out this technique by changing from one brand to another. Some products have advantages in switching brands

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and other brands also have several advantages to attract consumers (Sarsour & Muhammad Sabri, 2020). By employing Markov analysis, market share predictions for each brand will be assessed to determine whether a particular brand is a market leader, market challenger, market follower, or even niche market, which will then become the basis for the adoption of subsequent marketing strategies (Tak & Elliott, 2019; Yi-Chung et al., 2019).

Consumers consider product brands important because brand formation can add value, and professional marketers can create, maintain, protect, and promote brands (De la Torre et. al, 2020). A brand is a name, term, sign, symbol, design, or a combination of these, and they are intended to identify the products or services of one seller or sellers and differentiate them from those of competitors. A brand is a seller's promise to consistently convey attributes to buyers (Kavitha et. al, 2019). Brands have several purposes, including as an identity, which will make it easier for consumers to identify a product (Wei et. al, 2019; Inegbedion & Obadiaru, 2019), as promotional tools for product attraction (Ming-Huan et. al, 2021), tool to build an image by providing trust, quality assurance and certain prestige to consumers (Prabowo et al., 2020), and to control the market (Kailin et. al, 2021). Factories make products, while consumers buy brands and the best brand is the guarantee of quality, and, if competitors easily imitate a product, the brand always has a uniqueness that is relatively difficult to imitate (García-Galicia et. al, 2019). Brands are closely related to perception, hence competition between companies is a battle of perceptions, not just a battle of products.

In the highly competitive consumer products industry, effective marketing strategies are essential for optimising product marketing. This research aims to determine the most suitable marketing strategy for each detergent brand by analysing consumer reactions and responses to company-implemented marketing strategies. The objective is to assess consumer acceptance of existing detergent products and quantify market shares for specific brands using the Markov chain method. Additionally, the study seeks to identify and understand the relationships between dominant detergent attributes, such as cleaning efficacy, stain removal, odour prevention, fragrance, fabric softening, and product variety, potentially employing factor analysis. Knowing the market share and attributes that cause consumers to become loyal and which cause consumers to switch to other brands, can be used as a preference for producers to fulfil the attributes desired by consumers by considering various aspects such as costs and the company's technical capabilities.

2. Literature Review

Apergis et.al (2019) define consumer behaviour as the process a person goes through in searching for, purchasing, using, evaluating, and acting after consuming a product, service, or idea that is expected to meet their needs. Consumer behaviour studies how decision- makers, whether individuals, groups, or organisations, make purchasing decisions or purchase and consume products (Shen et. al, 2022). The concept of personal consumers in this definition can be explained as follows: consumers are individuals who buy goods and services for

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themselves, to meet family needs, and as gifts for others. Hence, private consumers buy products for personal use, and in this case individual consumers are end users (Arumugam & Rajathi, 2020).

From a marketing perspective, a market consists of all potential customers with specific needs or desires who may be willing and able to engage in exchange processes to satisfy and fulfill the desires (Askari et. al, 2019). Hence, market size depends on the number of people who have needs, and resources demanded by others, and are willing to offer these resources in exchange for satisfying consumer desires (Susanty et al., 2022). Consumer market behaviour is influenced by four main factors including culture, sub-culture, and social class. It is also influenced by society in terms of reference group, family, role and status, and personal comprising age and life cycle stage, occupation, economic conditions, and style. Moreover, consumer behaviour is also affected by life, personality and self-concept, and psychology which consists of motivation, perception, knowledge and beliefs (Osu et .al, 2019; Mallak & Abdoh, 2022).

Concerning the market, knowing the market share for a particular brand of product will determine the company's demand. Market share is a share of a company's total industry sales in a particular market (Yingchun et. al, 2020). The unit of sales can be in the form of branches or at a unit price, namely Rupiah in Indonesia. Market share data is primarily used to evaluate a company's marketing capabilities in increasing sales, and paying attention to the number of industry sales (Mahmoudi & Ghaneei, 2022). The data can also be used to understand the demand of companies (De la Torre et. al, 2020). Market share shows the company's strength by knowing how big the company is in meeting product needs. In this case, to achieve the marketing goals of a business, it is crucial to adopt the right marketing strategy with the right marketing logic. Hence decisions about a company’s marketing costs, marketing mix, and marketing allocations must be appropriately considered (Inegbedion & Obadiaru, 2019; Arumugam & Rajathi, 2020). It also refers to operational factors or implementation of marketing activities in determining a marketing mix such as pricing, packaging, branding, determining distribution channels, advertising, etc. (Apergis et. al, 2019).

About market share Markov Chain method constructs a transition probability matrix and then calculates the possibility of market share in the future. The analysis approach is a method that studies the properties of a variable in the present based on its properties in the past to estimate the properties of that variable in the future (Susanty et. al, 2022). The transition probability is an example of a change that a consumer might make from one brand to another (Inegbedion & Obadiaru, 2019). Consumers can switch from one brand to another due to advertising, special promotions, price, dissatisfaction, etc. This will be useful because the market share in the coming period can be calculated early. The Markov Chain method is widely used for decision-making but only provides information for decision-makers to improve their decisions, not solutions (Askari et. al, 2019). In the repeated probability calculations, it will be found in specific periods that the probability results of the analyses of

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the two matrices have the same value or are fixed or do not change when they are calculated for subsequent periods (Doroshkevych et.al, 2020), this condition is called steady-state probability (Revathy et. al, 2021). The steps to find the steady-state probability are the same as those to calculate the probability under certain conditions. The probability value will be the same after meeting the steady-state probability in subsequent periods (Ming-Huan et. al, 2021). Therefore, this probability can be used to predict the number in a steady state, multiplying the steady state probability by the number of people related to the problem being faced (Lakshmi & Jyothi, 2020).

In the present study, the assessment of market shares and brand preference using Markov analysis is applied to four detergent products comprising Rinso (R), Sp Klin (S), Attack (A), and Bu Krim (B). Rinso is a detergent product which is produced by PT Unilever Indonesia Tbk, and from 2018 to 2022, has a control of 26% in the East, while Sp Klin (S) detergent is a product of PT Wing Surya, from 2018 to 2022, and it has 23% control of the East Java market. Attack detergent product (A) was produced by PT. from 2018 to 2022, and it has 15% control of the East Java market, while Bu Krim (B) detergent which was produced by PT Total Chemindo Loka from 2018 to 2022 and it has 12% control of the East Java market. Meanwhile, the remaining 24% market share of the detergent products is controlled by other various brands.

3. Method and Analysis

In the present study, the classification of Markov processes can be distinguished based on the nature of the set of indices [T] [discrete parameters or continuous parameters], and the characteristics of state group [I] [discrete values/constant values] (Lakshmi & Jyothi, 2020). The stochastic process can be viewed as a function of two variables *t* and *s*, where the dominant *s* is the set *S* and the dominant *t* is the set of real numbers. The expression *x*(*t, si*) represents a single time function for a particular outcome *si*. For a given *ti* of prices, *x*(*ti, s*) is a quantity that depends on *s* and is called a random variable. Finally, *x(i, si*) is a pure number. We can use the notation *x(t)* to represent a stochastic process that eliminates its dependence on *s*. In this case, *x(t)* will inform four different things, namely: (i) a group of time functions (*t* and *s* are variables); (ii) a single time function (variable *t*, *s* fixed); (iii) random variables (fixed *t*, variable *s*) and (iv) single numbers (fixed *t*, fixed *s*).

A Markov process can be defined as a stochastic system with the characteristic that the occurrence of a state at a time depends on and only on the previous state. Therefore, if:

$t0 < 1 < \ldots < tn$ to all $n = 0, 1, 2, \ldots$.

At a given point in time, a set of random variables $\{x(tn)\}$ is a Markov process if it satisfies the following properties:

$P\{x(tn) = xn \mid x(tn-1) = xn\text{-}1, \ldots, x(t0)=x0\}$

$P\{x(tn) = xn \mid x(tn-1) = xn\text{-}1)$

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For anytime *t*, when the event is *x(t),* and all previous events are *x1, x2, …, xt* – 1 that occur from a known process, then the probability of all events is *x(t)* and does not depend on the previous events, but it depends on the closest previous state. In the Markov process, two important matrices must be formed first: the principal and transition of algebraic probability matrices (Wei *et.al*, 2019; Mallak & Abdoh, 2022). Table 1 demonstrates the Markov process classification that can be utilised.

Table 1. Markov Process Classification

		T	
1		Discrete	Continue
	Discrete	Parameter Discrete	Continue Parameter
Discrete	Discrete	Parameter	Continue Parameter

The study incorporates a comprehensive analysis involving multiple stages. Firstly, data validity and reliability analysis is conducted to assess the relationships between different variables and determine the validity and reliability of the obtained data. Following this, an analysis of significance level is employed to compare averages between product attributes and standards for non-product features. This study further delves into Markov chain analysis, emphasising the significance of Algebraic principal matrices, and transition probability matrices. These matrices are used to calculate market shares for each detergent product, forming the basis for tailored marketing strategies. The analysis progresses by utilising the First Order Markov Method, assuming relatively constant consumer movement patterns, and subsequently employing Higher Order Markov Analysis, considering external factors such as price fluctuations. Lastly, factor analysis is implemented to generate a positioning map for detergent products, elucidating consumer perceptions based on attribute assessments of similar product brands. This multi-stage approach offers a comprehensive understanding of the market dynamics, consumer behaviour, and strategic implications for detergent products.

The present research was conducted from June 2022 to August 2022, and it was carried out in eight (8) cities in East Java Province that are considered as representatives. The cities are Surabaya, Sidoarjo, Malang, Gresik, Tuban, Bojonegoro, Magetan and Madiun. The primary data is obtained directly from the responses of the participants via questionnaire, and they are collected and tabulated by giving a specific score or ranking. The sample of this study consists of 97 consumers who have used Rinso, So Klin, Bu Cream, and Attack detergent products.

3.1 Determination of Questionnaire Variables

The variables in the questionnaire include product attributes and non-product attributes. In this study, the variables include the detergents' ability to clean clothes, remove difficult stains, soften fabrics, provide fragrance to clothes, prevent unpleasant odours, produce abundant foam, eradicate germs, and produce variations in sizes, and prices. In comparison, non-product variables include promotion, influence from others, product availability in the market, and attractive packaging. A more detailed analysis is needed to quantify the level of "gain" or "loss between the four brands. This type of analysis is applied to

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determine how many consumers have left brand A and turned to brands B, C, or D. On the other hand, this analysis also functions to find out which additional number of customers for brand A come from which brand, whether it comes from brand B, C, or D.

Switching components or components that do not change can be investigated further after looking at the complex of, core components or groups that do not switch detergent brands. Hence, it is necessary to calculate the transition probability of the four brands. The probability that a particular brand will retain its loyal customers is defined as the transition probability. Information about changing patterns in detergent brands is identified from consumers' questionnaire surveys. Customer retention, and "gain" are shown through rows in the matrix, while the columns represent customer retention and loss. Overall, data related to changing detergent brands was obtained from survey results by distributing questionnaires to consumers.

3.2 Samples and Procedures

Table 2 demonstrates an overview of the intended distribution of the survey samples across various districts, reflecting the ambitious goal of obtaining responses from a total of 350 individuals. The selected regions comprising Surabaya, Sidoarjo, Malang, Gresik, Tuban, Bojonegoro, Magetan, and Madiun, encompass diverse populations. However, despite careful planning and allocation, the researchers had difficulty getting as many as 350 respondents. This is due to several reasons, including respondents not filling out the questionnaire completely, respondents not understanding the questions asked, respondents not responding or answering questions in the questionnaire submitted via Google Form, and, respondents not meeting the required criteria. The researchers decided to use an appropriate research sample and by the required criteria, including (1) respondents had used all product brands, namely Rinso, So Klin, Attack, and Bukrim; (2) respondents used each product more than three times; (3) respondents purchase products on their initiative.

Table 2. Pieces Take in Several Regions

No.	District	Total Population	Samples Taken
1.	Surabaya	5.756.835	67
2.	Sidoarjo	2.613.320	52
3.	Malang	3.082.533	49
4.	Gresik	2.735.104	36
5.	Tuban	1.503.862	44
6.	Bojonegoro	1.493.642	24
7.	Magetan	904.584	32
8.	Madiun	1.934.610	46
	Total		350

Based on the results of data collection that was carried out on 103 respondents from the distributed questionnaires, it turned out that six respondents chose a detergent brand other than the detergent brand which was the focus of the research. This is a limitation of the study. Then, the Main Algebraic Matrix can be created, which appears in Table 3 and will be used to

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describe the acquisition of market share and the pattern of change between each detergent brand analysed. These brands include Rinso (R), So Klin (S), Attack (A), and Bukrim (B). The information that can be obtained from Table 3 is that consumers who make purchases within a certain period only occasionally choose the same brand. For example, for the Rinso brand, the number of consumers in the first period was 43; in the second period, the number decreased to 37. This was caused by the addition or movement of consumers. 3 consumers of the So Klin brand switched to the Rinso brand, and 4 users of the Attack brand also switched to the Rinso brand. However, at the same time, 7 Rinso users switched from the Rinso brand and moved to the So Klin brand, and 6 Rinso users switched to the Attack brand. So in the second period, the total remaining Rinso brand users were 37 people. For other detergent brands, it can be interpreted and explained as above.

The results of data collection in Table 3 can be used to determine the market share gain for the initial period of purchasing each detergent brand. This can be done by calculating the quotient between the number of users for brand i and the total number of detergent users multiplied by 100%. The calculations correspond to the formulation for Markov Sequence Method One:

$$\text{Pi} = \frac{N_i}{N_{total}} \text{ x } 100\% \qquad \ldots\ldots\ldots\ldots\ldots (1)$$

For example, to calculate the market share in the initial period for the detergent brand R, the market share gain would be as follows:

$$\text{Pi} = \frac{43}{97} \text{ x } 100\% = 44.3\% \qquad \ldots\ldots\ldots\ldots\ldots (2)$$

The same thing can be done to obtain market share for other detergent brands so that a table of market share acquisition in the initial period for each brand is obtained which is shown in Table 4.

Table 3. Detergent Brand Switching Patterns

Brand	Number of Customer Periods I	In Addition to				Lost From				Number of Customers Period II
		R	S	A	B	R	S	A	B	
Rinso (R)	43	0	3	4	0	0	7	6	0	37
So Klin (S)	12	7	0	4	0	3	0	2	1	17
Attack (A)	33	6	2	0	2	4	4	0	4	31
Bukrim (B)	9	0	1	4	0	0	0	2	0	12
	97									97

Table 4. Table of Initial Market Share Gain

Brand of Detergent	Market Share in the Early Period
Rinso (R)	44.3 %
So Klin (S)	12.4 %
Attack (A)	34.02 %
Bukrim (B)	9.28 %

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3.3 Transition Probability Matrix

The Transition Probability Matrix below shows that there is a big opportunity for each brand and the probability of losing consumers who switch to other brands. To get the probability value in P, it can be done by dividing the number of users who remain in control during observation by the number of users in the initial purchase period. The probability calculation for each situation is as follows;

$$P = \begin{array}{c} \\ R \\ S \\ A \\ B \end{array} \begin{bmatrix} R & S & A & B \\ {}^{30}/_{43} = 0.698 & {}^{7}/_{43} = 0.163 & {}^{6}/_{43} = 0.139 & {}^{0}/_{43} = 0 \\ {}^{3}/_{13} = 0.25 & {}^{6}/_{12} = 0.5 & {}^{2}/_{12} = 0.167 & {}^{1}/_{12} = 0.083 \\ {}^{4}/_{33} = 0.121 & {}^{4}/_{33} = 0.121 & {}^{21}/_{33} = 0.636 & {}^{4}/_{33} = 0.121 \\ {}^{0}/_{9} = 0 & {}^{0}/_{9} = 0 & {}^{2}/_{9} = 0.222 & {}^{7}/_{9} = 0.78 \end{bmatrix}$$

Or more briefly written as follows;

$$P = \begin{array}{c} R \\ S \\ A \\ B \end{array} \begin{bmatrix} R & S & A & B \\ 0.698 & 0.163 & 0.139 & 0 \\ 0.25 & 0.5 & 0.167 & 0.083 \\ 0.121 & 0.121 & 0.636 & 0.121 \\ 0 & 0 & 0.222 & 0.78 \end{bmatrix}$$

3.4 First Order Markov Process

This process is used to find out how much each detergent brand has gained in terms of the market share in the first period, i.e. June 2022. Tables 5 present the acquisition of market share per period. The formulation is as follows;

1. The market share gain in June is as follows:

$$A_{(n)} = A_{(n-1)} .B$$

$$A_{(1)} = (0.443; 0.124; 0.340; 0.0928) \text{ x } \begin{bmatrix} 0.698 & 0.163 & 0.139 & 0 \\ 0.25 & 0.5 & 0.167 & 0.083 \\ 0.121 & 0.121 & 0.636 & 0.121 \\ 0 & 0 & 0.222 & 0.78 \end{bmatrix}$$

$$A_{(1)} = (0.381; 0.175; 0.319; 0.124)$$

2. The market share gain for each detergent brand in the second period is calculated as follows:

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Table 5. Table of Acquisition of Market Share per Period

Period	Brand			
	Rinso	So Klin	Attack	Bukrim
0	0.443	0.124	0.340	0.0928
1	0.381354	0.175349	0.319127	0.123816
2	0.348287	0.188202	0.312596	0.149844
3	0.328777	0.188597	0.311914	0.169697
4	0.314946	0.185716	0.313327	0.186039
5	0.304545	0.182055	0.315068	0.198391
6	0.296807	0.178667	0.316946	0.207661
7	0.288844	0.175984	0.318825	0.215454
8	0.2842	0.173585	0.320177	0.220907
9	0.280331	0.171891	0.320894	0.225542
10	0.27716	0.17036	0.321528	0.228617
11	0.274687	0.168992	0.322079	0.231571
12	0.273041	0.168166	0.3223	0.233252
13	0.271516	0.167461	0.322299	0.234646
14	0.270568	0.166798	0.322437	0.236123
15	0.26987	0.166635	0.32352	0.236903
16	0.269293	0.166593	0.323875	0.237024
17	0.268716	0.166551	0.323958	0.237925
18	0.268716	0.166551	0.323958	0.238705
19	0.268400	0.166275	0.324195	0.239201
20	0.268139	0.166114	0.324504	0.239605

The market share for the following month uses the same formulation to reach a steady state condition where the market share will not change implying that consumers will not change their choices. The same can be calculated for the next period as follows;

$$A_{(2)} = (0.381; 0.175; 0.319; 0.124) \text{ x } \begin{bmatrix} 0.698 & 0.163 & 0.139 & 0 \\ 0.25 & 0.5 & 0.167 & 0.083 \\ 0.121 & 0.121 & 0.636 & 0.121 \\ 0 & 0 & 0.222 & 0.78 \end{bmatrix}$$

$$A_{(2)} = (0.381 \,;0.175 \,;0.319 \,;0.124)$$

3.5 High Order Markov

The calculations in the high-level Markov use a probability matrix which is a different transition from the transition probability matrix that is utilised in the First-Order Markov. The analysis on high-level Markov is conducted to obtain the value of the new transition probability Matrix by taking into account the influence of external factors on the effect of price changes on each detergent brand. The price list for each detergent brand in August was

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obtained from several leading retailers in the East Java region. Unadjusted transition probabilities can be calculated to find a new Transition Probability Matrix.

$$\overline{P_{1j}} = P_{ij} + (S_{it} - \overline{S_{1t}})$$

= 0.698-0.05 (12400-11867)

= 25.95

In the same way, the unadjusted value of the displacement probability is obtained. This is shown in Tables 6a and 6b;

Table 6a. Table of Unadjusted Switching Opportunities

Probability	Value	Probability	Value
$\overline{P_{11}}$	25.95	$\overline{P_{21}}$	1.58
$\overline{P_{12}}$	5.49	$\overline{P_{22}}$	6.15
$\overline{P_{13}}$	5.469	$\overline{P_{23}}$	1.497
$\overline{P_{14}}$	5.33	$\overline{P_{24}}$	1.413
$\Sigma\, \overline{P_{1j}}$	42.24	$\Sigma\, \overline{P_{2j}}$	10.64

Table 6b. Table of Unadjusted Switching Opportunities (continue)

Probability	Value	Probability	Value
$\overline{P_{31}}$	32.79	$\overline{P_{41}}$	39.33
$\overline{P_{32}}$	32.79	$\overline{P_{42}}$	39.33
$\overline{P_{33}}$	162.714	$\overline{P_{43}}$	39.552
$\overline{P_{34}}$	32.79	$\overline{P_{44}}$	195.87
$\Sigma \overline{P_{1j}}$	261.084	ΣP4 j	314.082
$\Sigma\, \overline{P_{3j}}$	261.084	$\Sigma\, \overline{P_{4j}}$	314.082

Furthermore, to get the adjusted Pij, these numbers must be converted into one by dividing the adjusted transition probability value by the number of transition opportunity values in the same row, as follows;

$$P_{11} = \overline{P_{11}} \sum P_{ij} \quad = 25.95 / 42.24 = 0.614$$

In the same way, the adjusted transition probability values for all entries are obtained, as shown in Table 7 below;

Table 7. Table of Adjusted Turnover Opportunities

Peluang	Nilai	Peluang	Nilai
P11	0.614	P21	0.148
P12	0.129	P22	0.578
P13	0.129	P23	0.141
P14	0.126	P24	0.133
ΣP1j	1	ΣP2 j	1
P31	0.126	P41	0.125
P32	0.126	P42	0.125
P33	0.623	P43	0.126
P34	0.126	P44	0.624
ΣP3 j	1	ΣP4 j	1

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Therefore, the new Transition Probability Matrix is:

$$B_b = \begin{array}{c} \\ R \\ S \\ A \\ B \end{array} \begin{bmatrix} R & S & A & B \\ 0.614 & 0.129 & 0.129 & 0.126 \\ 0.148 & 0.578 & 0.141 & 0.133 \\ 0.126 & 0.126 & 0.623 & 0.126 \\ 0.125 & 0.125 & 0.126 & 0.624 \end{bmatrix}$$

Since A(2) = A(1) + B, the distribution of market share in the second period is as follows:
A(2) = A(1) . Bb

$$= (0.381; 0.175; 0.319; 0.124) \text{ x } \begin{bmatrix} 0.614 & 0.129 & 0.129 & 0.126 \\ 0.148 & 0.578 & 0.141 & 0.133 \\ 0.126 & 0.126 & 0.623 & 0.126 \\ 0.125 & 0.125 & 0.126 & 0.624 \end{bmatrix}$$

$$= (0.316; 0.206; 0.288; 0.189)$$

The calculation above shows that the market share in the second period for Rinso detergent brand is 31.6%, So Klin is 20.6%, Attack is 28.8%, and Bu krim is 18.9%. From the gains of the existing market share, it can be seen that even though the price of Bu krim detergent brand is lower, consumers still do not prefer this brand. This is caused by the possibility that other detergent brands are better even though they are more expensive than Bu krim brand.

3.6 Product and Non-Product Attributes

The level of importance is used to determine which attribute is most important to respondents when they want to use or buy detergents. The details that serve as case examples are divided into two parts; nine product-related features (product attributes) including clothes cleaning, tough stains, softening fabrics, determining good and preventing bad odours, producing abundant foam, and the ability to form a shield. Other than these elements, four attributes that affect non-product attributes, including promotion or advertising, influence from others, market availability, and attractive packaging are also considered. At the importance level, this is done by comparing the average value of product attributes, and non-product attributes to determine the consistency of these attributes.

The assessment of attributes is divided into two assessments, consisting of general assessment, and special assessment. Concerning the general assessment, this study managed to obtain the data from 97 respondents. In the assessment of certain attributes, the respondents who were assessed were loyal respondents, indicating that in the first period and the second period, they continued to use the same brand of detergent. General assessment refers to the opinions of all respondents regarding the attributes of the detergent based on the importance level of a feature which is shown in Table 8. It shows that of the 97 respondents, more consumers are concerned with the first product attribute which is the ability to clean the clothes. Table 8 also shows that the less important product attribute goes to product variations/types. Table 9 shows the assessment of the level of importance of non-product features. For the four non-product attributes, the non-product attribute that most

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influences consumers in purchasing or using detergent is the attribute of the availability of the product in the market.

Table 8. General Rating of Detergent Attributes

Product Attribute	Mean
cleaning clothes	6.4175
remove stubborn stains	6.3107
soften cloth	5.7670
scent clothes	5.6214
It prevents musty and unpleasant odours	5.8350
abundant foam	4.3398
capable of forming an anti-germ shield	5.3301
Product variations/types	4.2039
Price	5.5534

Table 9. General Assessment of Non-Product Attributes

Non-product Attribute	Mean
advertising promotion, the influence of others	3.9515
removes stubborn stains, softens fabrics	3.2233
availability on the market	5.4272
attractive packaging	3.3495

2. *Assessment of Loyalty*

a. For Loyal Respondents

The number of respondents who remain faithful or loyal to one detergent brand in the first period and second period in using detergent is 62. The level of importance of the attributes that cause respondents to remain loyal to one brand is shown in Table 10. Concerning Product Attributes, cleaning clothes remains the main priority for consumers in determining the brand of detergent they will use.

Table 10. Special Assessment of Detergent Attributes for Loyal Consumers

Product Attribute	Mean
cleaning clothes	6.53
remove stubborn stains	6.35
soften cloth	5.80
scent clothes	5.59
It prevents musty and unpleasant odours	5.85
abundant foam	4.53
capable of forming an anti-germ shield	5.45
Product variations/types	4.24
Price	5.53

Consumers are less focused on the variety/type of detergent product, while, the level of interest in non-product attributes can be seen in Table 11. Regarding non-

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product attributes, consumers remain loyal to one brand of detergent because the detergent used has the availability attributes in the market, in the sense that the detergent used is readily easy to obtain. It is found that consumers are less concerned about detergent packaging attributes in determining detergent choices.

Table 11. Special Assessment of Non-Product Attributes for Loyal Consumers

Non-product Attribute	Mean
Advertising promotion, the influence of others	4.23
Removes stubborn stains, softens fabrics	3.32
Availability on the market	5.47
Attractive packaging	3.18

b. For Disloyal Respondents

In this study, the survey discovers that there are 35 disloyal respondents, and Table 12 analyses the reasons why Rinso consumers switched to So Clin brand. The main cause that Rinso brand detergent consumers switch to So Klin brand is because they believe that So Klin cleans clothes better than Rinso brand detergent. Consumers also think that So Klin has a longer-lasting perfume scent that keeps clothes from smelling damp. It is shown that consumers give the second highest rating to this attribute after the first attribute. Meanwhile, on non-product attributes as shown in Table 13, consumers of Rinso detergent brand switch to So Klin brand because So Klin is more readily available than Rinso brand detergent. Consumers give a higher assessment of the availability of Product Attributes in the market, at 5.47 and they also think that promotions for So Klin are more interesting, memorable and quicker than promotions for Rinso brand detergent.

Table 12. General Assessment of Detergent Attributes for Rinso Consumers Who Move to So Klin

Product Attribute	Mean
cleaning clothes	6.53
remove stubborn stains	6.35
soften cloth	5.80
scent clothes	5.59
It prevents musty and unpleasant odours	5.85
abundant foam	4.53
capable of forming an anti-germ shield	5.45
Product variations/types	4.24
Price	5.53

Table 13. General Assessment of Non-Product Attributes for Rinso Consumers Who Move to So Klin

Non-product Attribute	Mean
advertising promotion, the influence of others	4.23
removes stubborn stains, softens fabrics	3.32
availability on the market	5.47
attractive packaging	3.18

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Table 14 lists the causes respondents switched from the Rinso detergent brand to the Attack brand. It can be seen that Rinso brand detergent consumers switch to Attack brand because they believe that Attack is better at cleaning clothes and removing difficult stains than Rinso brand detergent. Apart from that, Attack brand detergent is better at preventing damp and unpleasant odours because Attack formula can make the scent of clothes last longer than Rinso brand detergent.

Table 14. General Assessment of Detergent Attributes for Rinso Consumers Who Move to Attack

Product Attribute	Mean
cleaning clothes	6.50
remove stubborn stains	6.50
soften cloth	6.16
scent clothes	6.16
It prevents musty and unpleasant odours	6.50
abundant foam	5.00
capable of forming an anti-germ shield	4.83
Product variations/types	5.00
price	5.00

Table 15 shows consumers of the Rinso detergent brand switching to Attack brand because Attack is easier to find on the market, and Attack packaging is more attractive compared to Rinso brand detergent.

Table 15. General Assessment of Non-Product Attributes for Rinso Consumers Who Move to Attack

Attribute Non-product	Mean
advertising promotion, the influence of others	3.83
removes stubborn stains, softens fabrics	2.83
availability on the market	5.67
attractive packaging	2.83

Respondents from the So Klin detergent brand moved to the Rinso brand. This has caused consumers of the So Klin detergent brand to switch to the Rinso brand as shown in Table 16. It can be seen that the main cause So Klin detergent brand consumers to switch to Rinso brand is because they believe that Rinso brand detergent is better at cleaning clothes than So Klin brand detergent. Even though the price of Rinso brand detergent is higher than So Klin brand detergent (as seen in the detergent price list in the attachment), they prefer the Rinso brand.

Meanwhile, in non-product attributes, consumers of the So Klin detergent brand switched to the Rinso brand because Rinso was easier to find than So Klin brand detergent. Also, consumers of the So Klin detergent brand are more interested in the promotion/advertisement of Rinso detergent, which says "Daring to be dirty is good." It can be seen in Table 17.

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Table 16. General Assessment of Detergent Attributes for So Klin Consumers Who Move to Rinso

Product Attribute	Mean
cleaning clothes	6.67
remove stubborn stains	6.33
soften cloth	5.67
scent clothes	6.00
It prevents musty and unpleasant odours	6.00
abundant foam	5.00
capable of forming an anti-germ shield	5.33
Product variations/types	4.67
Price	6.67

Table 17. General Assessment of Non-Product Attributes for So Klin Consumers Who Move to Rinso

Non-product Attribute	Mean
advertising promotion, the influence of others	5.33
removes stubborn stains, softens fabrics	4.67
availability on the market	5.67
attractive packaging	3.67

In Table 18 the reason So Klin detergent brand consumers switch to Attack brand is because they believe that Attack is more capable of cleaning clothes, removing difficult stains, and softening fabrics than So Klin brand detergent. Even two So Klin consumers who switched to the Attack brand did not care about the price of Attack detergent which is far more expensive than So Klin brand detergent.

Table 18. General Assessment of Detergent Attributes for So-Clin Consumers Switching to Attack

Product Attribute	Mean
cleaning clothes	6.50
remove stubborn stains	6.50
soften cloth	6.50
scent clothes	6.00
It prevents musty and unpleasant odours	6.00
abundant foam	5.50
capable of forming an anti-germ shield	5.50
Product variations/types	4.00
price	5.50

In Table 19 on non-product attributes, consumers of the So Klin detergent brand switch to Attack brand because Attack is readily available and easier to find on the market than So Klin brand detergent, and they prefer the packaging of Attack brand detergent to So Klin brand detergent.

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Table 19. General Assessment of Non-Product Attributes for So-Clin Consumers Switching to Attack

Non-product Attribute	Mean
advertising promotion, the influence of others	4.00
removes stubborn stains, softens fabrics	3.50
availability on the market	6.00
attractive packaging	4.00

From Table 20, it can be explained that the main cause So Klin detergent brand consumers switch to Bu Krim brand is because they believe that Bu Krim is better at cleaning clothes than So Klin brand detergent. In addition, Bu Krim brand detergent as seen in the detergent price list is much cheaper than So Klin brand detergent.

Table 20. General Assessment of Detergent Attributes for So Klin Consumers Moving to Bukrim

Product Attribute	Mean
cleaning clothes	6.00
remove stubborn stains	7.00
soften cloth	5.00
scent clothes	4.00
It prevents musty and unpleasant odours	5.00
abundant foam	3.00
capable of forming an anti-germ shield	6.00
Product variations/types	5.00
price	7.00

Meanwhile, as shown in Table 21 on non-product attributes, consumers of the So Klin detergent brand switched to the Bu Krim brand because it is easier to find in the market than So Klin brand detergent. When reversed, they are less influenced by promotions/advertising and less influenced by others changing their choices.

Table 21. General Assessment of Non-Detergent Attributes for So Klin Consumers Moving to Bu krim

Non-product Attribute	Mean
advertising promotion, the influence of others	1.00
removes stubborn stains, softens fabrics	1.00
availability on the market	5.00
attractive packaging	3.00

Table 22 shows the data about Attack brand detergent respondents who moved to Rinso because their consumers believe that Rinso is better at cleaning clothes than Attack brand detergent. The non-product attributes relating to consumers of Attack brand detergent that switch to Rinso brand because Rinso is easier to find in the market than Attack in Table 23. While Table 24 shows that the main cause Attack detergent brand consumers switch to So Klin brand is because consumers believe that So Klin can

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better remove difficult stains than Attack brand detergent. Table 25 presents the non-product attribute that causes Attack brand detergent consumers to switch to So Klin brand because So Klin is easier to find in the market than Attack brand detergent.

Table 22. General Assessment of Detergent Attributes for Attack Consumers Who Move to Rinso

Product Attribute	Mean
cleaning clothes	6.50
remove stubborn stains	6.00
soften cloth	5.75
scent clothes	6.00
It prevents musty and unpleasant odours	5.75
abundant foam	6.00
capable of forming an anti-germ shield	5.50
Product variations/types	4.00
price	6.00

Table 23. General Assessment of Non-Detergent Attributes for Attack Consumers Who Move to Rinso

Non-product Attribute	Mean
advertising promotion, the influence of others	3.75
removes stubborn stains, softens fabrics	4.25
availability on the market	5.25
attractive packaging	4.25

Table 24. General Assessment of Detergent Attributes for Attack Consumers Who Move to So Klin

Product Attribute	Mean
cleaning clothes	6.00
remove stubborn stains	6.50
soften cloth	6.00
scent clothes	5.50
Prevents musty and unpleasant odours	5.50
abundant foam	3.25
capable of forming an anti-germ shield	5.50
Product variations/types	3.25
price	5.50

Table 25. General Assessment of Non-Detergent Attributes for Attack Consumers Moving to So Klin

Non-product Attribute	Mean
advertising promotion, the influence of others	3.75
removes stubborn stains, softens fabrics	4.25
availability on the market	5.25
attractive packaging	4.25

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3.7 Factor Analysis

In this study, factor analysis serves as a comprehensive method to elucidate the intricate relationships among several variables, specifically focusing on four observed detergent brands. The dataset derives from attribute assessments gathered through questionnaires distributed to the detergent users. The initial stage involves the meticulous selection of variables for inclusion in factor analysis, emphasising a requisite strong correlation between them. Variables displaying a weak correlation, indicated by a Measure Sampling Adequacy (MSA) value of less than 0.5 with others, face exclusion from subsequent calculations. Following variable selection, the chosen variables undergo extraction into one or more factors, forming the basis for further analysis. Once the factors are established, the subsequent steps involve the attribution of names to these factors, a process that includes variable selection and grouping.

In this specific study, comprising 13 influential attributes encompassing both product and non-product attributes, the data processing reveals a favourable MSA value of 0.780 in the KMO and Bartlett Tests, surpassing the threshold of 0.5. The absence of variables with MSA values below 0.5, as confirmed by the Anti-Image matrix table, ensures that none of the attributes will be excluded after the factors are extracted. The forthcoming elucidation of these 13 characteristics in the position map promises a comprehensive understanding of the intricate relationships among the detergent brands based on the attributes formed during the analysis. Table 26 presents the initial factor and the attributes.

Table 26. Initial Factor

No.	Factor	Attributes
1.	Quality Factor	Cleans clothes, removes tough stains, softens fabrics, scents clothes, and prevents damp and unpleasant odours.
2.	External Factor	Promotion, influence from other people, attractive packaging.
3.	Supporting Factor	Availability on the market, price.
4.	Powered Factor	Variations/types of products can form an anti-germ barrier.

3.8 Variable Extraction

After the variables are formed, the next step is to determine the attribute coordinates, which describe the position map of the attributes contained in the detergent product. From Table 2, it can be seen that several characteristics have a value of (-). This indicates that the features with these values have a weak correlation. This will have an impact on uncertainty as to whether the attribute with the (-) sign is included in factors 1, 2, 3, and 4. Therefore, it is necessary to carry out a rotation process to have clearer differences between variables in factors 1, 2, 3, or 4. The rotation results are shown in Table 27 below.

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Table 27. Table of Matrix Component

	Component			
	1	2	3	4
Cleaning clothes	.858	-.162	-.011	.072
Remove stubborn stains	.854	-.233	.046	.086
Soften cloth	.647	-.469	0.50	-.138
Scent clothes	.747	-.179	-.357	-.367
It prevents musty and unpleasant odours	.835	-.152	-.369	-.154
Abundant foam	.491	.510	-.202	127
Capable of forming an anti-germ shield	.476	-.096	-.032	.673
Product variations/types	.429	.385	.183	.500
Price	.290	-.368	.421	.069
Advertising promotion of the influence of others	.566	.565	.217	-.183
Removes stubborn stains, softens fabrics	.316	.704	.310	-.340
Availability on the market	.472	-.199	.659	-.150
Attractive packaging	.421	.455	-.250	.052

Extraction Method: Principal Component Analysis.
Four components were extracted.

Table 27 and Table 28 demonstrate that the factors that have the potential to cause consumers of Rinso products to switch to other detergent products are due to lack of fulfilment of product variations/types aspects such as to remove stubborn stains, and softening fabrics. Meanwhile, So Klin products cause consumer switching due to lack of fulfilment of the Soften cloth, capability of forming an anti-germ shield, and product variations/types aspects. Regarding the Attack brand, consumer switching happens due to a lack of fulfilment of the aspects of scent clothes, removing stubborn stains, and softening fabrics. The Bu Cream brand caused consumers to switch due to a lack of fulfilment of the abundant foam and attractive packaging aspects. However, in general, the aspects that need to be improved for all detergent brands are softening cloth and scent clothes and It prevents musty and unpleasant odours because all brand consumers still feel that the performance of these aspects is not optimal.

Table 28. Rotated Matrix Component

	Component			
	1	2	3	4
Cleaning clothes	.704	.184	.375	.312
Remove stubborn stains	.696	.132	.376	.387
Soften cloth	.676	-.062	.061	.438
Scent clothes	.904	.171	-.069	.017
It prevents musty and unpleasant odours	.909	.165	.162	.008
Abundant foam	.264	.540	.373	-.241
Capable of forming an anti-germ shield	.228	-.091	.785	.112
Product variations/types	-.022	.393	.672	.098
Price	.139	-.113	.124	.595
Advertising promotion of the influence of others	.199	.803	.124	.139
Removes stubborn stains, softens fabrics	-.040	.887	-.097	.097
Availability on the market	.175	.220	.015	.800
Attractive packaging	.271	.476	.270	-.276

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 6 iterations.

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4. Conclusion

Quality factors obtained include cleaning clothes, removing stubborn stains, softening fabrics, making clothes smell good, and preventing musty and unpleasant odours. External factors include promotional attributes, the influence of other people, and attractive packaging. Supporting factors include market availability and price attributes. In comparison, the last factor is the strength factor with variations/types and forms an anti-germ shield. These factors include all features, both product attributes and non-product attributes contained in detergent formulas. The results of the analysis using the Markov chain method show that consumers move in each period according to their needs. This happens until the condition of the market is stable, where Rinso brand during the stability period occupied the position of market challenger with a market share of 26.8%. So Klin as a market pitcher in the period of market stability and gained a market share of 16.6%, Attack in a condition of market stability occupied a position as a market leader and won a market share of 32.4%, Bukrim as a follower market, gained a market share of 23.9%.

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