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Identification of Consumer Purchase Intention Factors and Interactions for Fresh Milk Product

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Abstract

The purpose of this paper is to examine the significant relationships among the factors influencing consumers' purchase intention for fresh milk products and identify behavioural differences across age-based generation tiers and income levels. One of the main reasons is low consumer demand for fresh milk has driven up product-return rates. The experiment involved 482 respondents located at the Indonesian cities of Jakarta, Bogor, Depok, Tangerang, and Bekasi who indicated a preference for consuming fresh milk. Participants were asked to complete a questionnaire of the study. The results show that each hypothesised relationship is both positive and significant. Perceived product quality and extrinsic product cues first build consumers' trust. This strengthened trust—together with social influence and an individual's desire to consume—enhances perceived behavioural control, which proves to be the most powerful driver of purchase intention, while Social Influence also boosts purchase intention directly. Multi-Group Structural Equation Modelling shows that the effect of product quality on trust and social influence on purchase intention varies across generations. Consumers with higher incomes place greater value on product quality and extrinsic cues, while lower-income lean more on social influence when deciding to buy fresh milk. This research enriches the Theory of Planned Behavior by integrating cognitive (product quality, extrinsic cues), social, and personal (consumption drive) factors in SEM model—first in the fresh-milk category—analyzing their stability across age and income groups. It reveals how the balance between cognitive product evaluation and social pressure changes with demographic characteristics in shaping consumers' purchase intentions for fresh milk.

Keywords: Fresh Milk, Consumption and Purchase Intention, Age-Based Gen Differences, Income Level Differences, Multi Group Analysis

INTRODUCTION

The global food-supply chain faces a serious challenge in Food Loss and Waste (FLW) at every stage—from production and post-harvest handling to distribution and consumption(Anand & Barua, 2022; Wunderlich & Martinez, 2018; Xue et al., 2017). In Indonesia, a BAPPENAS (2021) report estimates that 23 to 48 million tonnes of food are lost or wasted each year, equivalent to 115–184 kilograms per capita. Drawn from 146 food commodities, these figures point to substantial nutritional, economic, and environmental losses that urgently need to be addressed.

FLW are different but connected. Food loss happens during production and post-harvest stages, while food waste occurs in distribution, retail, and consumer levels. Over the past decade, Food loss share has fallen from 61% in 2000 to 45% in 2019, while food waste share has risen from 39 percent to 55%—indicating that retail and consumption for the largest proportion of waste (Boiteau & Pingali, 2023).

FMCG products are characterized by mass production, high turnover, and short shelf life (Cha & Park, 2019). One of the leading FMCG products is fresh milk, whose consumption is increasing rapidly along with awareness of the importance of health and nutrition.The tight competition in this industry encourages manufacturers to develop innovative sales strategies to attract consumer interest (Bahety et al., 2024). By meeting consumer needs, satisfaction can be achieved while preventing food waste (Kumar et al., 2017). Indonesia's fresh-milk market has expanded in tandem with growing consumer awareness of health and nutrition, yet it continues to suffer high product-return rates. Internal data from FMCG firm show an average return rates of 23% between January and August 2024, peaking at 33% in August. These returns erode profit margins, raise logistics costs, depress customer satisfaction, and exacerbate supply-chain inefficiencies (Lynce et al., n.d.). Monthly spikes in returns point to mismatches between supply and actual demand, highlighting the need for deeper consumer-behaviour analysis.

Age and income are key demographic factors in understanding consumer behavior in the FMCG sector, particularly when analyzed through the lens of life stage and economic capacity. (Kotler & Keller, 2016) explain that age segmentation reveals distinct behavioral patterns, each generation's unique life experiences shape their specific needs, requiring marketers to tailor products accordingly (Agustina et al., 2024), while consumer needs evolve with age (Rayi & Aras, 2021). Meanwhile, income segmentation highlights purchasing power and consumer priorities, significantly influencing product preferences and consumption patterns (Kotler & Keller, 2016). Strategy segmentation allows marketers to focus efforts on segments that have the greatest market potential, depending on the type of product being offered (De & Van Wyk, n.d.). The Theory of Planned Behavior (TPB), developed by (Ajzen, 1991) adds perceived behavioral control to explain how individuals assess their ability to perform a behavior. TPB includes attitudes, subjective norms, and perceived behavioral control, all shaping behavioral intentions (Fai Cheung & K-S Chan, 2000). In the FMCG sector, this model helps explain quick, repetitive purchasing decisions influenced by product perceptions (Adhikary & Kar, 2018), social pressures (Helen & Darling Selvi, 2022), and perceived ease or affordability. Together, these factors significantly affect consumer purchase intentions, particularly for new products.

To accommodate the complexity of the TPB latent constructs and the moderating effects of age and income, SEM is an appropriate analytical technique that allows simultaneous estimation of a network of interrelated latent variables. This method allows the analysis of the relationship between one or more independent variables, which can be continuous or discrete, and one or more dependent variables, which can also be continuous or discrete (Ullman & Bentler, 2012). SEM supports multi-group analysis, allowing researchers to test whether the strength or significance of TPB paths differ across pre-defined demographic segments. By combining rigorous construct validation, overall model fit assessment, and subgroup comparisons within a single framework, SEM provides theoretical clarity and practical relevance for mapping the drivers of fresh milk purchase intentions across consumer profiles.

Based on this gap, this research utilizes SEM)to map the complex relationships between cognitive, social, and personal factors with the intention to purchase fresh milk, while also examining the moderating roles of age and income level. The SEM approach allows researchers to simultaneously test the conceptual model, measure construct validity, and evaluate cross-group differences. The results are expected to provide data-based insights for industry players to design segment-specific marketing strategies, reduce market returns, and improve the efficiency of fresh milk distribution in developing markets such as Indonesia.

The research aims to examine the factors influencing consumer purchase intentions for fresh milk in developing markets like Indonesia by analyzing the complex relationships between cognitive, social, and personal factors, with a focus on how these variables affect purchase decisions. Specifically, the research will explore how perceived product quality, extrinsic cues, and social influences interact, while also investigating the moderating roles of age and income level. In the end, this research will help companies in the fresh milk industry gain a deeper understanding of consumer preferences and demand, allowing them to tailor their marketing efforts more effectively to specific market segments.

RESEARCH METHODS

Hypothesis and Conceptual Model

The resulting conceptual model will be empirically tested using Structural Equation Modeling (SEM) to evaluate construct validity, estimate the strength of each hypothesised path, and investigate the moderating effects of age and income level. Figure 1 illustrates the conceptual model of this study and hypothesis statement to be tested.

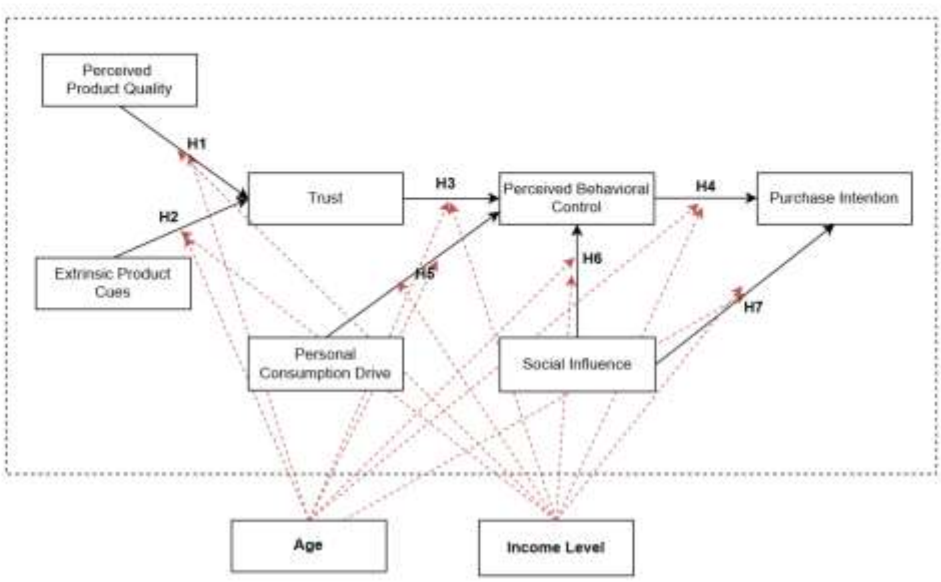

Figure 1. Proposed Conceptual Model

The conceptual model provides a description of the link between the factors that influence the intention to purchase fresh milk products, with age and income level serving as moderator variables. This model also assists in the analysis of disparities in the manner in which these factors influence purchasing decisions across individuals of varying ages and income levels. Building on the theoretical foundations outlined above, this study proposes seven hypotheses to capture the key relationships among trust, perceived behavioural control, personal consumption drive, social influence, and purchase intention. The alternative hypothesis statement to be tested is as follows:

H1 Trust in perceived product quality has a positive effect on overall trust.
H2 Trust in extrinsic product cues has a positive effect on overall trust.
H3 Trust has a positive influence on perceived behavioural control.
H4 Perceived behavioural control positively influences purchase intention.
H5 Personal consumption drive positively influences perceived behavioural control.
H6 Social influence positively influences perceived behavioural control.
H7 Social influence positively influences purchase intention.

Sampling and Data Collection

This research employs a cross-sectional quantitative survey methodology aimed at people who consume fresh milk in the Jabodetabek region (DKI Jakarta, Bogor, Depok, Tangerang, Bekasi). A pilot test involving 50 respondents was done prior to the main survey to evaluate item clarity, content validity, and internal consistency of the questionnaire. According to the recommendations of Hair et al. (2021), which stipulate a minimum of ten respondents per indicator for optimal maximum likelihood estimate, the requisite sample size is calculated as 31 indicators multiplied by 10, resulting in 310 respondents. The pilot test results were utilized to enhance the phrasing and response scale

Sampling was executed purposively, with quotas modified according to demographic characteristics, specifically age generations and income level categories. The quota proportions are derived using the 2023 demographic statistics of Jabodetabek provided by the Department of Population and Civil Registration to guarantee the representation of each sector. Data collecting occurred from January to February 2025 via an online questionnaire on Google Forms, disseminated through social media, community forums, and professional networks to engage diverse societal groups.

The distributed questionnaires produced 482 complete replies, exceeding the minimum need and guaranteeing adequate statistical power for SEM analysis. The data obtained are representative of the Jabodetabek population for each demographic characteristic. This pie chart delineates the demographic features of the respondents, including gender, age, and income distribution.

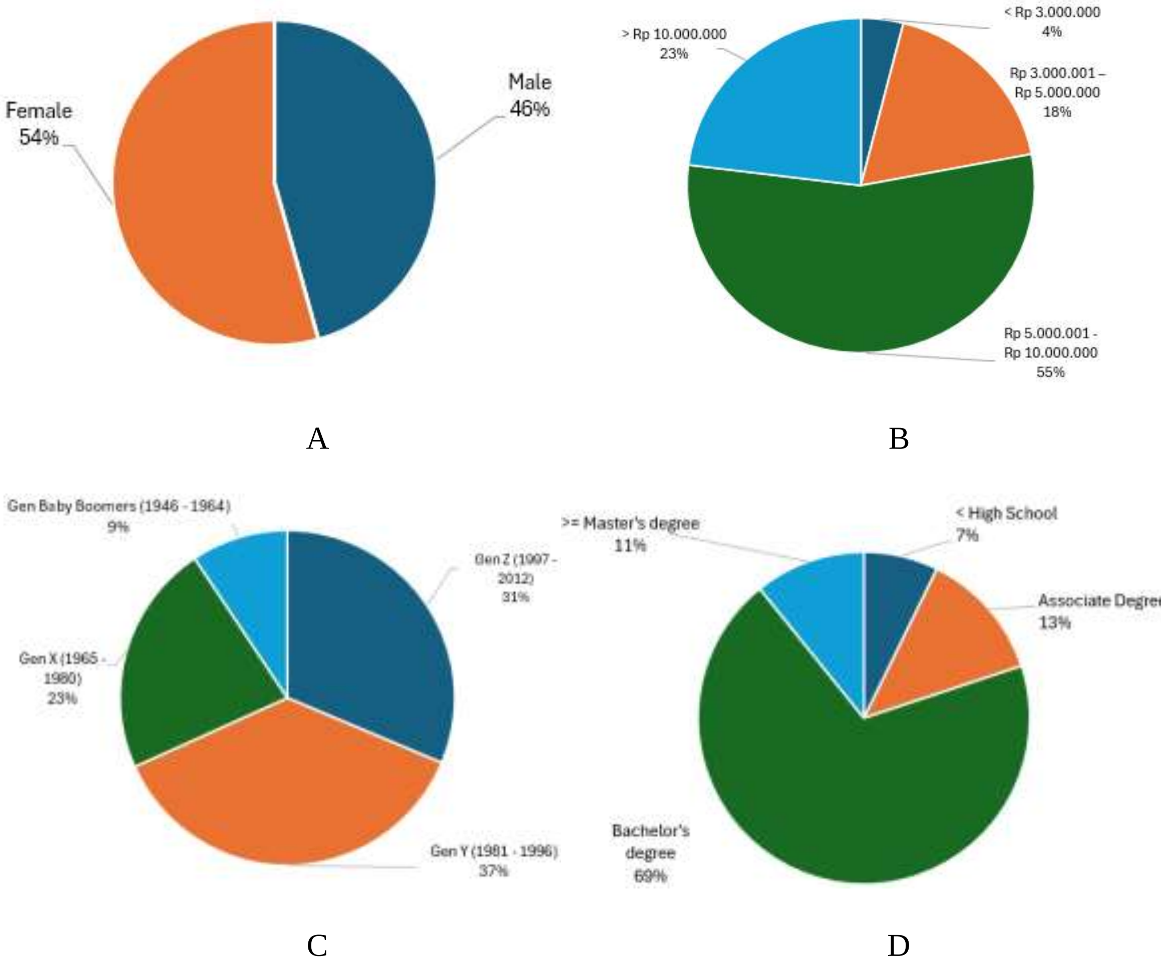

Figure 2. Distribution of Sample Characteristics:
(A) Sample by Gender; (B) Sample by Income Level; (C) Sample by Birth Generation; (D) Sample by Educational Attainment.

RESULT AND DISCUSSION

Model specification

The conceptual framework and hypotheses H1–H7 were converted into a Structural Equation Modeling (SEM) format comprising two primary components: the measurement model, which encapsulates seven latent constructs represented by validated and reliable measurable indicators, and the structural model, which highlights the causal relationships among constructs in accordance with the hypotheses while incorporating the moderating effects of age and income level through interactions among constructs. The ultimate model is depicted in a path diagram to enhance the assessment of goodness-of-fit and the calculation of relationship coefficients.

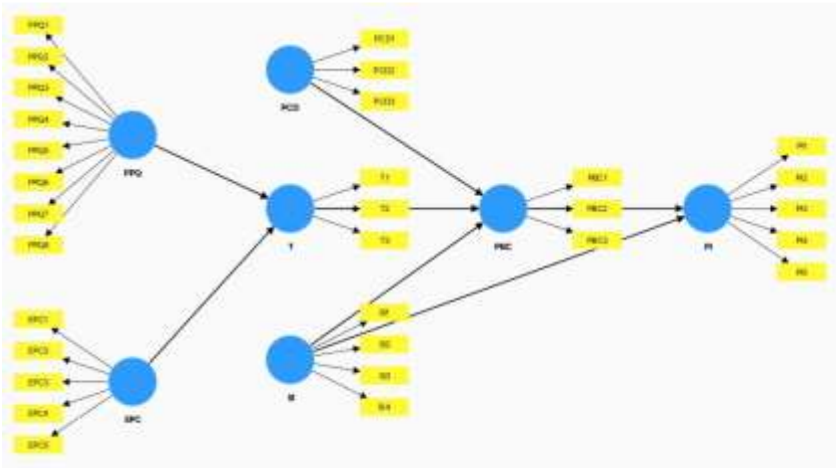

Figure 3. Initial research model

Convergent validity

The validity of this study was assessed by evaluating the Average Variance Extracted (AVE) value. The AVE value of each latent variable is the primary determinant of construct validity. For convergent validity to be established, the AVE value must exceed 0.5. In Table 1, it can be seen that the AVE value for the PPQ variable is <0.5, so it is necessary to check and improve the model.

Table 1. Convergent Validity Test Results

	Cronbach's alpha	***Composite reliability* (rho_a)**	***Composite reliability* (rho_c)**	***Average variance extracted* (AVE)**
PBC	0.703	0.704	0.835	0.628
EPC	0.823	0.828	0.876	0.588
PI	0.790	0.793	0.856	0.544
PPQ	0.840	0.847	0.877	0.473
PCD	0.706	0.713	0.836	0.630
SI	0.710	0.711	0.821	0.534
T	0.715	0.722	0.839	0.635

Table 2. Outer Loading Value of Each Indicator

Indikator	***Outer Loading***	**Indikator**	***Outer Loading***	**Indikator**	***Outer Loading***
PBC1	0.792	**PI4**	0.763	**PCD2**	0.798
PBC2	0.785	**PI5**	0.694	**PCD3**	0.752
PBC3	0.799	**PPQ1**	0.770	**SI1**	0.737
EPC1	0.833	**PPQ2**	0.761	**SI2**	0.719
EPC2	0.723	**PPQ3**	0.714	**SI3**	0.744
EPC3	0.698	**PPQ4**	0.622	**SI4**	0.722
EPC4	0.833	**PPQ5**	0.681	**T1**	0.779
EPC5	0.737	**PPQ6**	0.671	**T2**	0.800

Indikator	***Outer Loading***	**Indikator**	***Outer Loading***	**Indikator**	***Outer Loading***
PI1	0.698	**PPQ7**	0.609	**T3**	0.811
PI2	0.760	**PPQ8**	0.657		
PI3	0.768	**PCD1**	0.829		

Numerous indicators exhibit outer loading levels below 0.7, shown in red in Table 2, including EPC3 (0.698), PI1 (0.698), PI5 (0.694), PPQ4 (0.622), PPQ5 (0.681), PPQ6 (0.671), PPQ7 (0.609), and PPQ8 (0.657). Consequently, it is imperative to modify the model at this juncture by eliminating indications that fail to satisfy the requisite values. The subsequent results pertain to the model respecification adjusted for the outer loading value.

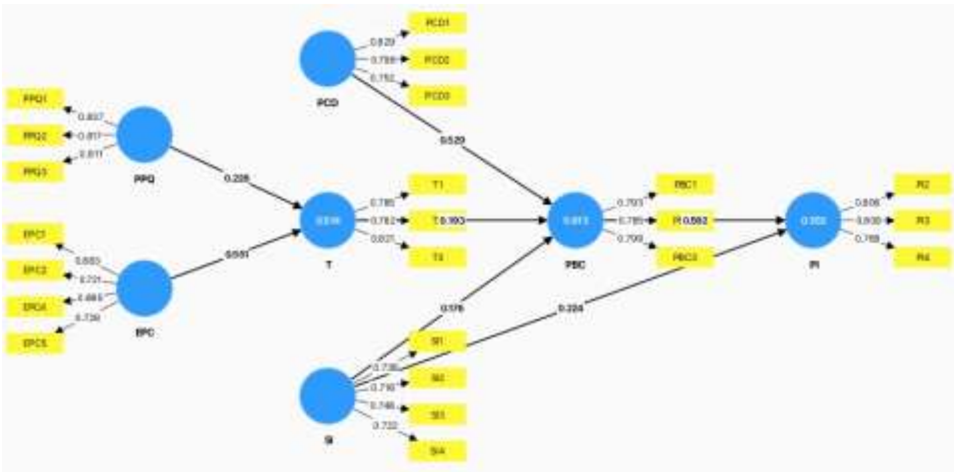

Figure 4. Model for Respecification Results

Subsequent to the removal of indicators EPC3 (0.698), PI1 (0.698), PI5 (0.694), PPQ4 (0.622), PPQ5 (0.681), PPQ6 (0.671), PPQ7 (0.609), and PPQ8 (0.657), the subsequent action is to evaluate the acquired test findings. Modifications to the indicators inside the model will result in variations in the revised AVE values for each latent variable. Consequently, assessing these modifications is crucial to confirm the integrity of the revised model. The subsequent table presents the outcomes of the convergent validity assessment following the model respecification process, it can be seen that the AVE value for each variable is >0.5.

Table 3. Convergent Validity Test Results After Respecification

	Cronbach's alpha	***Composite reliability (rho_a)***	***Composite reliability (rho_c)***	***Average variance extracted (AVE)***
PBC	0.703	0.704	0.835	0.627
EPC	0.820	0.834	0.882	0.653
PI	0.721	0.722	0.843	0.641
PPQ	0.760	0.762	0.862	0.676
PCD	0.706	0.713	0.836	0.630
SI	0.710	0.711	0.821	0.534

	Cronbach's alpha	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*	*Average variance extracted (AVE)*
T	0.715	0.728	0.838	0.634

Discriminant validity

Discriminant validity testing is a method used to assess the extent to which a notion in a research model is truly separate from other constructs. The validity can be evaluated by many basic methods, namely the cross-loading method, Fornell-Larcker Criterion, and Heterotrait-Monotrait Ratio (HTMT). Robust discriminant validity guarantees that each construct inside the model is distinctly separate and does not intersect with other constructs, hence enhancing the precision and comprehension of the research outcomes.

This study employed the Fornell-Larcker Criterion test, wherein the diagonal values highlighted in green represent the square root of the Average Variance Extracted (AVE) for each latent variable. Discriminant validity is achieved when the square root of the AVE value exceeds the correlation between other latent variables in the respective row and column.

Table 4. Discriminant Validity Test Results

	PBC	**EPC**	**PI**	**PPQ**	**PCD**	**SI**	**T**
PBC	**0.792**						
EPC	0.747	**0.808**					
PI	0.721	0.741	**0.801**				
PPQ	0.698	0.631	0.729	**0.822**			
PCD	0.752	0.798	0.721	0.697	**0.794**		
SI	0.571	0.569	0.563	0.555	0593	**0.731**	
T	0.593	0.695	0.652	0.576	0.616	0.423	**0.796**

Table 4 displays the outcomes of the discriminant validity assessment employing the Fornell-Larcker Criterion technique, with the diagonal values highlighted in green representing the square root of the AVE for each latent variable. Discriminant validity is achieved when the square root of the AVE exceeds the correlation with other latent variables in the respective row and column. This signifies that each latent variable has a stronger association with its respective indicators than with other variables, hence satisfying the criteria for discriminant validity.

Result

Based on the results of the hypothesis test, all relationships between latent variables in the research model show a high level of significance. This is indicated by the t-statistic value that far exceeds the threshold of 1.96 and a p-value of 0.00, which is less than 0.05, thus all the tested hypotheses can be accepted at a 95% confidence level. The strongest relationship is seen between the PBC variable and PI with a t-statistic value of 15.696, followed by PCD against PBC (14.324) and EPC against T (12.697), indicating significant influence between constructs.Meanwhile, other relationships, such as PPQ to T, SI to PBC, SI to PI, and T to PBC, also show strong significance with t-statistic values above 5.These results indicate that the independent variables in the model have a significant contribution to the dependent variables they are associated with, thereby supporting the validity of the theoretical model developed in this research.

Table 5. Hypothesis Test Result

	T statistic	*P values*	**Assessment**
PBC → PI	15.696	0.00	Fail to Reject
EPC →T	12.697	0.00	Fail to Reject
PPQ →T	5.211	0.00	Fail to Reject
PCD → PBC	14.324	0.00	Fail to Reject
SI → PBC	5.057	0.00	Fail to Reject
SI → PI	5.814	0.00	Fail to Reject
T →PBC	5.536	0.00	Fail to Reject

Multi-group analysis

This study used age groups and income levels as moderating variables to discern heterogeneity in the interactions among variables, so enhancing the comprehension of consumer behavior across different segments. The moderation test results, categorized by age groups, revealed substantial disparities in various relational pathways among components. Notable disparities were seen in the pathways Perceived Behavioral Control (PBC) → Purchase Intention (PI) and Extrinsic Product Cues (PE) → Trust (T) among the Baby Boomer and Gen X cohorts, as well as between the Baby Boomer and Gen Y cohorts, with a p-value of 0.001.

The outcomes of the moderation test concerning income levels revealed substantial disparities in the pathways Perceived Product Quality (PPQ) → Trust (T) and Trust (T) → PBC when comparing income groups (Rp 3.000.001 – Rp 5.000.000)-(> Rp 10.000.000) and (Rp 5.000.001 hingga Rp 10.000.000)-(> Rp 10.000.000), with (>Rp 10.000.000) denoting the higher income group. The results demonstrate that the impact of trust and personal participation on perceived behavioral control is contingent upon the consumer's purchasing power. Consequently, these findings offer a segmentation-oriented methodology for marketing communication strategies and product creation.

The results of the Multi-Group Analysis (MGA) also provide valuable insights into the differences among age groups and income levels in processing information and making purchasing decisions. The Baby Boomer and Gen X generations are more influenced by cognitive attributes such as product quality and brand trust, but younger generations like Gen Y and Gen Z exhibit a greater reliance on social influences and personal consumption impulses.

In the context of income, consumers with high incomes are more receptive to cognitive signals such as the clarity of label information, nutritional value, and product safety. On the other hand, consumers with low incomes have a tendency to rely on social influence in order to shape their trust and intents to make a purchase. In general, this research is able to successfully integrate the Theory of Planned Behavior with important variables in the context of the local Indonesian environment.

CONCLUSION

The main finding of this study is the dominant role of perceived behavioral control as the primary determinant of purchase intention. This reflects that consumers who perceive themselves as possessing the ability, access, and convenience to consume fresh milk tend to exhibit a higher purchase intention. The illusion of control over consumption behavior significantly influences the final purchasing decision. Consequently, perceived control over consumption behavior is a significant determinant affecting the ultimate purchase decision. Moreover, social influence has been demonstrated to affect purchase intentions directly and indirectly by enhancing perceived behavioral control. Recommendations from acquaintances, relatives, and exposure to social trends and marketing on social media have been shown to affect consumers' beliefs in their capacity to consistently consume fresh milk. This phenomenon is particularly relevant in the contemporary digital age, as the views and actions of social groups frequently act as the principal reference in consumption decisions.

Furthermore, the study offers a conceptual model that may be utilized in various FMCG product sectors and emphasizes that demographic segmentation-based marketing strategies (age and income) are essential for effectively responding to market dynamics, particularly in mitigating the mismatch between actual demand and the supply of fresh dairy products, which has historically resulted in a high return rate in the domestic market.

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