

The Influence of Conventional and Digital Marketing Strategies on Commercial Vehicle Buying Interest in Increasing Commercial Vehicle Sales

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ABSTRACT

This study aims to analyse the impact of conventional and digital marketing strategies on consumer purchase intention in increasing commercial vehicle sales, with purchase intention serving as a mediating variable. A quantitative approach was employed using an explanatory research design. Data were collected through purposive sampling from 111 respondents, consisting of consumers who have either purchased or not yet purchased Hino brand commercial vehicles, including trucks and buses. The collected data were analysed using Structural Equation Modelling (SEM). The findings reveal that both conventional and digital marketing strategies have a positive and significant influence on consumer purchase intention, which in turn directly and indirectly contributes positively to sales performance. Furthermore, purchase intention acts as a significant mediating variable between marketing strategies and vehicle sales. The study concludes that purchase intention plays a crucial mediating role in the relationship between marketing strategies and the increase in commercial vehicle sales. These findings provide valuable insights for commercial vehicle dealers in selecting and implementing appropriate marketing strategies, particularly in leveraging both conventional and digital media to enhance consumer purchase intention and drive sales growth.

Keywords: Conventional Marketing Strategy, Digital Marketing Strategy, Purchase Intention, Commercial Vehicle.

I. Introduction

The automotive industry, particularly the commercial vehicle sector such as trucks and buses, plays an important role in driving economic growth in Indonesia. Trucks and buses are widely used across various sectors, including logistics, construction, mining, and the distribution of both people and goods. The demand for these vehicles continues to increase in line with infrastructure development and domestic trade activities. However, despite the large market potential, the commercial vehicle sales industry such as trucks and buses still face various challenges that hinder its growth. Many logistics companies experience difficulties in procuring new trucks and buses due to increasingly strict tonnage regulations. Some entrepreneurs in the construction sector also face obstacles in obtaining trucks through flexible credit schemes, thereby delaying projects that require heavy vehicles. In addition, poor road conditions in several regions, such as Sumatra and

Kalimantan, lead to higher vehicle maintenance costs, affecting the operational efficiency of transportation companies. Meanwhile, companies that previously relied on trucks for goods distribution have begun shifting to other modes of transportation, such as railways, which offer lower operating costs.

Furthermore, competition in the truck industry has become increasingly intense with the entry of various new brands, particularly from China, which offer more competitive prices. The shift in trends toward alternative transportation models, such as railways and ships for long-distance goods distribution, also affects the demand for trucks. The truck industry's dependence on certain sectors, such as mining and construction, further causes demand for these vehicles to be unstable. Similarly, in the bus transportation sector, several consumers particularly within government institutions have started transitioning from diesel-engine buses to imported electric vehicles (EVs). This shift has, to some extent, eroded the domestic market share of locally manufactured buses. Below is sales data information for commercial vehicles trucks and buses from Gaikindo (Indonesian Automotive Association) based on wholesales (Factory to Dealer) in 2023 and 2024.

Table 1. Commercial Vehicles Sales Data in Indonesia

No.	Brand	Qty 2023 (units)	Qty 2024 (units)	Difference (Unit)	Growth (%)
1	Mitsubishi Fuso	31.553	27.721	-3.832	-12%
2	Isuzu	31.427	26.379	-5.048	-16%
3	Hino	28.449	24.158	-4.291	-15%
4	UD Trucks	1.799	1.960	161	9%
5	Mercedes-Benz CV	2.070	1.551	-519	-25%
6	FAW	617	847	230	37%
7	Tata	31	1	-30	-97%
8	Scania	714	436	-278	-39%
Total Commercials		96.660	83.053	-13.607	-14%
Total Sales (CV & Passenger)		1.005.802	865.762	-140.040	-14%

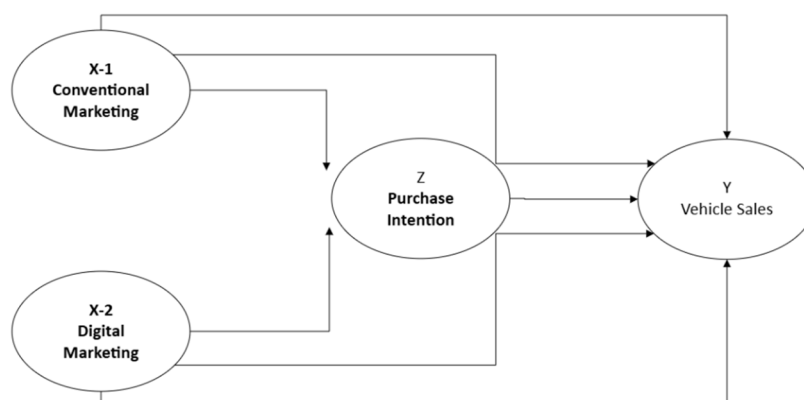
Source: Gaikindo 2023 and 2024

Based on Gaikindo's data, it was reported that from January to December 2024, total car sales in terms of wholesales decreased by 14% compared to the same period in 2023. This aligns with the overall decline in vehicle sales, which also fell by 14%. According to Gaikindo, this was caused by sluggish market conditions due to weakening consumer purchasing power and declining market sentiment. Although specific data for the commercial segment is not always separately published, Gaikindo stated that commercial vehicles experienced a decline of around 15% in 2024 (including commercial vehicles beyond the eight products listed in the table above), consistent with the overall downward trend in Indonesia's new vehicle market. In facing these conditions, along with various challenges in the automotive industry particularly in commercial vehicle sales appropriate strategies are needed to enhance the competitiveness of Indonesia's truck and bus sales industry. One key factor in boosting sales is the implementation of effective marketing strategies. A combination of conventional and digital marketing provides a solution to reach a wider range of customers and increase sales conversion. Conventional marketing through automotive exhibitions, dealer networks, direct visits by salespeople, and advertising in traditional media remains relevant in building customer trust. Meanwhile, digital marketing strategies such as website optimization, social media utilization, email marketing, and promotional videos can expand market reach and foster broader interaction with potential customers. By implementing well-integrated marketing strategies, the commercial vehicle industry in Indonesia can strengthen its competitiveness, reach more customers across the country, and promote a more stable and sustainable market growth.

II. Literature Review and Hypothesis Development

Research by (Akbar, 2023) shows that marketing strategies have a significant influence on purchasing decisions in the commercial vehicle sector. Factors such as product quality, competitive pricing, effective promotion, and wide distribution play a role in attracting customers and increasing sales. (Akbar, 2023) highlights that product, price, promotion, and distribution variables in the marketing mix positively and significantly influence purchasing decisions, with price being the most dominant factor. This study also confirms that effective marketing strategies can increase customer interest and commercial vehicle sales. The objective of this research is to identify and explore the impact of Conventional Marketing Strategies (X1), Digital Marketing (X2), and Purchase Intention (Z) on Commercial Vehicle Sales (Y) at Hino dealerships in the Greater Jakarta (Jabodetabek consist of Jakarta Bogor Depok Tangerang and Bekasi) area. The conceptual framework of this study illustrates the correlation between the variables, where conventional and digital marketing strategies influence purchase intention, which in turn affects vehicle sales.

In the purchasing decision-making process, conventional marketing (X1) plays an important role as a medium for direct interaction with customers, influencing their level of interest. Meanwhile, digital marketing (X2) can reach a broader and more distant consumer base while providing a more interactive experience to enhance purchase intention (Z) by demonstrating the advantages and quality of the product. Purchase intention functions as a mediator between conventional and digital marketing and commercial vehicle sales (Y).



Picture 1. Relationship Concept of Variables

Source: Visualization data from SmartPLS4, 2025

Marketing strategy is one of the key factors in the success of dealerships in selling vehicles to consumers. Marketing serves as both a strategy and a tool to deliver messages to others with the aim of eliciting responses that align with the marketer's expectations. Conventional marketing continues to play an important role in the automotive industry, particularly in building brand awareness, consumer trust, and encouraging purchasing decisions. In the automotive sector, conventional marketing strategies influence vehicle sales through various long-established direct approaches. Furthermore, in the context of automotive marketing, conventional strategies also include proper market segmentation by aligning marketed products with consumer needs, which enables companies to enhance their competitiveness and market position. Special offers during exhibitions, such as discounts or giveaways, also serve as effective promotional strategies to boost sales (Oktaria et al., 2024).

H1: Conventional marketing strategies have a positive effect on commercial vehicle sales.

Digital marketing strategies influencing vehicle sales in Indonesia have become a crucial element in addressing changing consumer behavior and the challenges of the modern automotive market. In today's era,

social media played a vital role in communication. Commonly used platforms such as Facebook, Instagram, TikTok, and YouTube are utilized to enhance brand awareness and consumer engagement. These strategies include creating appealing visual content, running paid advertising campaigns (e.g., Instagram and Facebook Ads), as well as collaborating with automotive influencers to expand market reach and build consumer trust (Adhawayah & Anshori, 2019). Research on digital marketing and its influence on vehicle sales indicates that the use of social media, website optimization, and other digital strategies significantly contribute to improving consumer purchase decisions and expanding market share. However, prior studies have not specifically examined commercial vehicles; therefore, this study emphasizes the role of digital marketing in commercial vehicle sales.

H2: Digital marketing strategies have a positive effect on commercial vehicle sales.

Previous research by Prasetyo found that conventional marketing mixes, such as promotion, market segmentation, and competitive pricing, significantly contributed to increasing automotive product sales ((Khadiqi, DF., Kusmayati, NK., Kurniawan, Y., Kurniawan, T., Wulansari, 2024). Exhibitions and vehicle demonstrations provided opportunities for consumers to directly view and test products, which enhanced trust and purchase intention.

H3: Conventional marketing strategies have a positive effect on consumer purchase intention.

Research by Lestari identified that digital marketing through online platforms and social media has become an essential aspect of expanding market reach and strengthening brand awareness ((Khadiqi, DF., Kusmayati, NK., Kurniawan, Y., Kurniawan, T., Wulansari, 2024). A study by (Triyono et al., 2022) highlighted the importance of social-interactive marketing strategies in promoting electric cars in Indonesia, finding that social media marketing increased awareness and purchase intention, with 50% of respondents identifying social media as their primary source of information about electric vehicles.

H4: Digital marketing strategies have a positive effect on consumer purchase intention.

The influence of purchase intention on vehicle sales growth has been widely studied and consistently demonstrates a significant positive relationship. Purchase intention reflects a psychological factor representing a consumer's willingness to buy a particular product, which ultimately affects purchasing decisions and vehicle sales volume. Research by (Heru et al., 2022) revealed that consumer purchase intention is influenced by factors such as price, promotion, and advertising, which directly enhance purchasing decisions for motor vehicles.

H5: Consumer purchase intention has a positive effect on commercial vehicle sales.

Further evidence comes from research on Toyota Veloz dealerships by Pramesti (2023), confirming that sales promotions positively and significantly influence customer purchase intention, which in turn mediates the effect of promotions on purchasing decisions. This supports the notion that purchase intention is an important mediating variable in the relationship between conventional marketing and vehicle sales. Theoretically, Schiffman and Kanuk (2008) argue that purchase intention represents a positive attitude and consumer desire toward a product that drives individuals to make a purchase. Thus, effective conventional marketing should be able to enhance purchase intention to achieve significant sales growth.

H6: Purchase intention mediates the effect of conventional marketing strategies on commercial vehicle sales.

Purchase intention also functions as a mediating variable linking the influence of digital marketing to vehicle sales. Research by (Amalana, 2022) on the Shopee e-commerce platform showed that promotions and digital marketing positively and significantly affect purchasing decisions through the mediation of purchase intention. Conceptually, digital marketing strategies such as social media, electronic word of mouth (e-WOM), and other forms of digital promotion do not directly increase sales but rather enhance consumer purchase intention, which subsequently drives purchasing decisions.

H7: Purchase intention mediates the effect of digital marketing strategies on commercial vehicle sales.

III. Research Method

This study employs a quantitative approach with an explanatory research design aimed at examining the influence of conventional and digital marketing strategies on consumer purchase intention in increasing the sales of commercial vehicles, specifically trucks and buses. The study applies descriptive statistical analysis to present, illustrate, summarize, and describe research data obtained from observations and questionnaire responses from participants during the research process. The data presentation includes mean, median, minimum, maximum, standard deviation, number of observations from respondents, and so on (Ghozali, 2016). The research was conducted on consumers who had or had not purchased commercial vehicles, within the age group of 25–45 years, located in the Jabodetabek area. For data collection, this study utilized an online questionnaire accessed through the Microsoft Form platform, which contained statements based on four variable indicators: conventional marketing, digital marketing, purchase intention, and vehicle sales. These were structured using a five-point Likert scale ranging from “strongly agree” to “strongly disagree.” The sample was determined using a random sampling technique, targeting consumers of official Hino dealers in the Jabodetabek area, including both employees and owners who had or had not purchased and used Hino commercial vehicles. The survey was conducted over a two-month period. A total of 111 respondents participated, which was deemed sufficient to conduct Structural Equation Modeling analysis based on Partial Least Squares (J. Hair & Alamer, 2022). Data analysis was performed using SmartPLS4 software, covering validity testing, reliability testing, as well as examination of relationships among latent variables and mediation effects.

IV. Result and Discussion

Most respondents in this study were male (81%), while female respondents accounted for only 19%. In terms of age distribution, 9% were under 25 years old, 27% were between 25–35 years old, 39% were in the 36–45 years age group, and 26% were above 45 years old. These results indicate that the most dominant group of respondents was adults aged 36–45 years, representing the largest proportion of survey participants.

Table 2. The Data Description

		Respondent	Percent
Sex	Man	92	81%
	Women	22	19%
Age	<25 years	9	8%
	25-35 years	32	27%
	36-45years	43	39%
	>45 yeas	30	26%
Occupation	Entrepreneur	17	15%
	Employee	75	66%
	Army/Police/Officer	18	16%
	Others	4	3%

Have you ever a Hino Truck?	Yes	24	22%
	Not yet	90	78%
Have you ever a Hino Bus?	Yes	21	19%
	Not yet	93	81%
Have you ever seen Hino advertisement in media?	Yes	104	93%

Source: SmartPLS4 data, 2025

Based on the data, the most respondents were employees, accounting for 66%, making them the most dominant group in the survey. These employees also play an influential role in the decision-making process for vehicle purchases within their companies. Furthermore, 78% of respondents reported that they had never purchased a Hino truck, while 81% had never purchased a Hino bus. Interestingly, 93% of respondents indicated that they had seen Hino vehicle advertisements in the media. This finding suggests that Hino's marketing efforts, particularly through advertising, have indirectly reached the most respondents as potential customers.

Table 3. Type of Respondent Data

Name	Missing	Mean	Median	Scale Min	Scale Max	Std Deviation
X1-1	0	3.982	4	1	5	1.112
X1-2	0	3.473	4	1	5	1.204
X1-3	0	3.445	4	1	5	1.149
X1-4	0	3.864	4	1	5	1.171
X1-5	0	3.709	4	1	5	1.216
X2-1	0	3.927	4	1	5	1.126
X2-2	0	4.064	4	1	5	1.122
X2-3	0	3.591	4	1	5	1.162
X2-4	0	3.691	4	1	5	1.142
X2-5	0	3.364	3	1	5	1.118
Y1	0	3.700	4	1	5	1.083
Y2	0	3.373	4	1	5	1.127
Y3	0	3.664	4	1	5	1.073
Y4	0	4.000	4	1	5	1.079
Y5	0	3.909	4	1	5	1.058
Z1	0	3.509	4	1	5	1.118
Z2	0	3.764	4	1	5	1.061
Z3	0	4.000	4	1	5	1.044
Z4	0	3.891	4	1	5	1.056
Z5	0	3.591	4	1	5	1.131

Source: SmartPLS4 data, 2025

The research data were analyzed using descriptive statistics to illustrate and summarize the sample data in a straightforward manner without the need for generalization to a broader population. According to Ghozali (2016), descriptive statistics are employed to collect, organize, summarize, and present data so that it becomes more meaningful and easier for users to understand, while only providing a general description of the research object without generalizing about the population. Similarly, Sugiyono (2007) as cited in (Perdana et al., 2020) stated that descriptive statistics function to describe or provide an overview of the research object through sample or population data, but not to draw conclusions that apply universally. Based on the data table, all research variables had no missing values (missing value = 0), indicating that the dataset was complete. The mean values of the indicators ranged between 3.364 and 4.064, with the median consistently at 4 (except for indicator X2-5, which had a median of 3). This suggests that respondents tended to assign relatively high scores to the measured indicators, leading to the conclusion that consumer perceptions of the

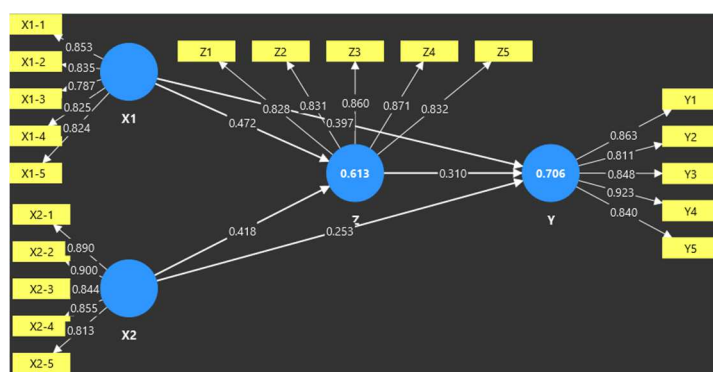
research variables fall within a favorable category. The moderate standard deviation values indicate consistency in the respondents' answers, demonstrating that the data is reliable for further analysis. Overall, the research instrument used met the descriptive validity and reliability criteria, in line with the principles of modern quantitative research (J. Hair & Alamer, 2022); (Sugiyono, 2022).

Table 4. Outer Loading

	X1 - Conventional Marketing	X2 - Digital Marketing	Y - Vehicle Sales	Z - Purchase Intention
X1-1	0.853			
X1-2	0.835			
X1-3	0.787			
X1-4	0.825			
X1-5	0.824			
X2-1		0.890		
X2-2		0.900		
X2-3		0.844		
X2-4		0.855		
X2-5		0.813		
Y1			0.863	
Y2			0.811	
Y3			0.848	
Y4			0.923	
Y5			0.840	
Z1				0.828
Z2				0.831
Z3				0.860
Z4				0.871
Z5				0.832

Source: SmartPLS4 data, 2025

J. F. Hair et al., (2019), as cited in Sayyida, (2023), state that an acceptable outer loading value is ≥ 0.70 , as this threshold indicates that the indicator demonstrates adequate convergent validity in measuring its construct. Referring to this standard, the data analysis results presented in the table above show that the average outer loading values for all indicators exceed 0.70. This implies that all indicators in this study can be considered valid in representing their respective variables. These findings are consistent with previous research, which suggests that indicators with outer loading values above 0.70 should be retained in the model since they have satisfied the requirements of convergent validity (J. F. Hair et al., 2019). Therefore, all indicators are deemed appropriate for use and can be carried forward in the subsequent stages of analysis.



Picture 2. PLS Algorithm Diagram

Source: SmartPLS4 data, 2025

The figure above illustrates the structural model (inner model) and the measurement model (outer model) using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach in SmartPLS4. This visualization depicts the relationships among the variables Conventional Marketing Strategy (X1), Digital Marketing Strategy (X2), Purchase Intention (Z), and Commercial Vehicle Sales (Y), along with the manifest indicators of each variable.

Table 5. Validity and Reliability Test

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
X1	0.883	0.884	0.914	0.680
X2	0.913	0.918	0.935	0.741
Y	0.910	0.913	0.933	0.736
Z	0.899	0.900	0.926	0.713

Source: SmartPLS4 data, 2025

Validity and reliability testing in quantitative research serves to ensure that the instruments used accurately measure what they are intended to measure (validity) and produce consistent data (reliability). The table above presents the results of validity and reliability testing for variables X1, X2, Y, and Z, based on several key statistical indicators, namely Cronbach's alpha, composite reliability (rho_a and rho_c), and average variance extracted (AVE). The results indicate that all variables (X1, X2, Y, and Z) met the criteria for strong reliability (Cronbach's alpha and composite reliability > 0.70) as well as adequate convergent validity (AVE > 0.50). Therefore, the research instrument used in this study can be considered valid and reliable for quantitative analysis. These findings are consistent with the recommendations of Hair et al. (2019) and Fornell & Larcker (1981), who emphasize that instruments with high reliability and validity values enhance the credibility of research outcomes and the generalizability of findings.

Table 6. Fornier Larcker Criterion

	X1	X2	Y	Z
X1	0.825			
X2	0.547	0.861		
Y	0.752	0.680	0.858	
Z	0.701	0.676	0.759	0.845

Source: SmartPLS4 data, 2025

The table above presents the correlation matrix among the variables Conventional Marketing (X1), Digital Marketing (X2), Purchase Intention (Z), and Vehicle Sales (Y), which is commonly used to assess discriminant validity in quantitative research models, particularly through the Fornell-Larcker Criterion. According to Fornell and Larcker (1981), the square root of the Average Variance Extracted (AVE) for each construct should be greater than its correlations with other constructs in the model, as evidence of discriminant validity (Henseler et al., 2015). Based on the data in the table, all diagonal values are consistently higher than the correlations between constructs within the same row or column. For instance, the square root of AVE for X1 (0.825) is greater than its correlations with X2 (0.547), Y (0.752), and Z (0.701). A similar pattern is observed across the other constructs. These results confirm that each construct demonstrates satisfactory discriminant validity, as the square root of AVE for every construct exceeds its correlations with other constructs. Therefore, each construct in this study can be clearly distinguished from the others under examination.

Table 7. Heterotrait – Monotrait Ratio (HTMT)

	X1	X2	Y	Z
X1				
X2	0.601			
Y	0.837	0.739		
Z	0.781	0.743	0.837	

Source: SmartPLS4 data, 2025

Discriminant validity serves to assess the extent to which constructs in a model are empirically distinct from one another. One of the more sensitive and recently recommended methods is the HTMT (Heterotrait-Monotrait Ratio of Correlations). According to Henseler et al., (2016), HTMT is a more reliable approach compared to the Fornell-Larcker criterion and cross-loadings, as it is more effective in detecting the lack of discriminant validity. All HTMT values in the table above are below the threshold of 0.90, with most also falling below 0.85. This indicates that there are no issues of discriminant validity among the constructs examined. Hence, all constructs in this research model meet the criteria for satisfactory discriminant validity. Consequently, each construct can be clearly distinguished from the others, with no conceptual overlap occurring between them.

Table 8. Collinearity Statistics (VIF) – Inner Model Matrix

	X1	X2	Y	Z
X1			2.003	1.427
X2			1.879	1.427
Y				
Z			2.586	

Source: SmartPLS4 data, 2025

The table above presents the values of the Variance Inflation Factor (VIF) used to evaluate potential multicollinearity issues among the variables in the inner model of the Structural Equation Modelling (SEM) analysis. VIF measures the extent to which the variance of a regression coefficient is increased due to correlations among predictors in the model. High VIF values indicate multicollinearity, which can affect the stability and interpretation of the model (J. F. Hair et al., 2019). Based on the results in the table, no multicollinearity issues were detected among the variables in the inner model. All VIF values fall below the critical threshold of 5.0, indicating that the model is stable and the estimated regression coefficients can be reliably interpreted.

Table 9. Collinearity Statistics (VIF) – Outer Model List

	VIF
X1-1	2.475
X1-2	2.152
X1-3	1.848
X1-4	2.120
X1-5	2.036
X2-1	2.981
X2-2	3.394
X2-3	2.247

X2-4	2.533
X2-5	2.233
Y1	2.658
Y2	2.387
Y3	2.493
Y4	4.172
Y5	2.643
Z1	2.235
Z2	2.259
Z3	2.792
Z4	2.763
Z5	2.313

Source: SmartPLS4 data, 2025

In the context of the measurement model (outer model), the Variance Inflation Factor (VIF) is used to identify potential multicollinearity among indicators within a construct. A high VIF value indicates that indicators are highly correlated with each other, which may obscure the interpretation of construct validity. Based on the results of the collinearity statistics (VIF) presented in the table, the majority of indicators show VIF values below 3.3, suggesting no significant multicollinearity. Two indicators (X2-2 and Y4) recorded VIF values slightly above 3.3, but still within the acceptable tolerance threshold; however, they require closer attention in subsequent validity testing and interpretation. Therefore, the indicators within the latent constructs are considered acceptable for inclusion in the structural model and do not interfere with the estimation of latent relationships.

Table 10. Coefficient Determinant R-square

	R-square	R-square-adjusted
Y	0.706	0.697
Z	0.613	0.606

Source: SmartPLS4 data, 2025

The coefficient of determination (R-square or R^2) is used to measure the extent to which independent variables explain the variance of dependent variables in the structural model. The R^2 value ranges from 0 to 1, with general interpretation according to Hair and Alamer (2022): $R^2 = 0.75$ indicates substantial explanatory power; $R^2 = 0.50$ indicates moderate; and $R^2 = 0.25$ indicates weak. Based on the calculation results, the structural model demonstrates strong predictive power for the variables Vehicle Sales (Y) and Purchase Intention (Z). The constructs Conventional Marketing (X1) and Digital Marketing (X2) jointly provide a substantial contribution in explaining the variance of Commercial Vehicle Sales and Purchase Intention. Furthermore, the adjusted R^2 values, which do not differ significantly from the R^2 values, indicate that the model is stable and not biased by the number of indicators.

Table 11. F Test

	X1	X2	Y	Z
X1			0.267	0.403
X2			0.116	0.317
Y				
Z			0.126	

Source: SmartPLS4 data, 2025

Based on the table, it can be concluded that there are positive relationships among all research variables. Conventional Marketing (X1) shows a relatively strong correlation with Commercial Vehicle Sales (Y) at 0.267 and with Consumer Purchase Intention (Z) at 0.403. Meanwhile, Digital Marketing (X2) also demonstrates positive relationships with Sales (Y) at 0.116 and with Purchase Intention (Z) at 0.317. Furthermore, Consumer Purchase Intention (Z) itself correlates positively with Sales (Y) at 0.126. These results indicate that both conventional and digital marketing strategies contribute to increasing consumer purchase intention and commercial vehicle sales, with conventional marketing exerting a relatively stronger influence compared to digital marketing within the context of this study.

Table 12. Predictive Relevance (Q2)

	Q²predict	RMSE	LM_MAE
Y1	0.461	0.802	0.688
Y2	0.433	0.856	0.734
Y3	0.477	0.783	0.687
Y4	0.583	0.704	0.603
Z1	0.394	0.832	0.738
Z2	0.392	0.882	0.737
Z3	0.375	0.846	0.672
Z4	0.395	0.820	0.682

Source: SmartPLS4 data, 2025

All indicators show positive Q² predict values, with Y1 to Y4 ranging between 0.433 and 0.583, and Z1 to Z4 ranging between 0.375 and 0.395. These results indicate that the model demonstrates adequate predictive ability across all indicators of Y (Sales) and Z (Purchase Intention). Based on the Q² predict test results, it can be concluded that the structural model employed possesses sufficient predictive relevance for the indicators of constructs Y (Sales) and Z (Purchase Intention). Since all indicators have Q² predict values greater than 0, the model fulfils the requirement of predictive relevance, as suggested by Shmueli et al. (2019). Although some differences were observed between RMSE and LM_MAE values, no significant deviations were detected, thus confirming that the model remains predictively stable.

Table 13. PLS Predict MV Summary PLS SEM

	Q²predict	RMSE	MAE
Y	0.646	0.612	0.491
Z	0.564	0.681	0.478

Source: SmartPLS4 data, 2025

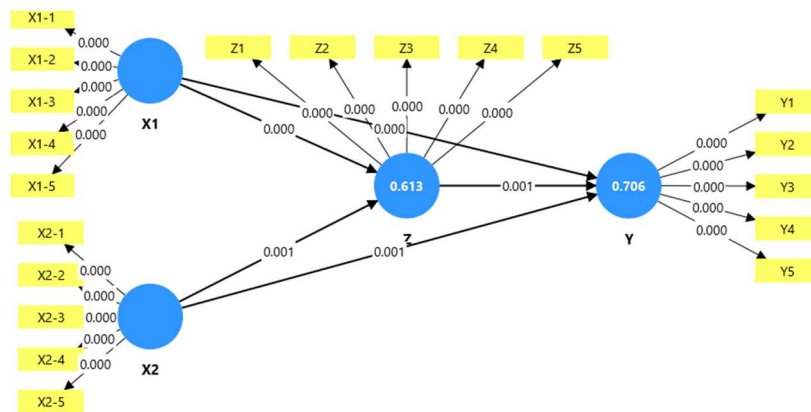
Based on the table above, the tested model demonstrates strong predictive ability for both vehicle sales (Y) and purchase intention (Z). Variable Y has a Q² predict value of 0.646, while variable Z has 0.564. Q² predict values exceeding 0.50 indicate that the model possesses significant predictive capability (J. F. Hair et al., 2019). This finding suggests that the model can explain more than 50% of the variance in out-of-sample data, thereby reflecting a high predictive power (Shmueli et al., 2015). The RMSE for variable Y is 0.612, which is lower than that for variable Z (0.681). This supports the notion that RMSE is a crucial metric for evaluating prediction errors, with smaller RMSE values indicating greater accuracy in out-of-sample predictions (Shmueli et al., 2015). Similarly, J. F. Hair et al., (2019) argue that lower RMSE values signify superior predictive accuracy. The MAE values for Y (0.491) and Z (0.478) are relatively low. MAE represents the average absolute error, and smaller values suggest higher predictive accuracy (Shmueli et al., 2016). According to J. F. Hair et al., (2019), MAE is also an essential metric for assessing model predictive performance, where lower values indicate minimal prediction deviations and robust model accuracy.

Table 14. Model Fit Test

	Saturated Model	Estimated Model
SRMR	0.059	0.059
d_ ULS	0.739	0.739
d_ G	0.422	0.422
Chi_square	250.227	250.227
NFI	0.858	0.858

Source: SmartPLS4 data, 2025

Based on the results in the table above, the SRMR value of $0.059 < 0.08$ indicates that the model exhibits a good level of fit with the data. This means that the model is well aligned with the observed data. According to Hu & Bentler (1999) in Henseler, Ringle, et al., (2016), SRMR measures the average difference between the observed covariances and those predicted by the model. An SRMR value < 0.08 suggests a good model fit. The NFI value of 0.858, which is close to the minimum threshold of 0.90, further indicates that the model is reasonably well fitted. Moreover, the consistent values of d_ ULS and d_ G between the saturated and estimated models reinforce the stability of the estimated model. These findings are consistent with Henseler, Ringle, et al., (2016) and J. F. Hair et al., (2020), who emphasize that $SRMR < 0.08$ and NFI values approaching 0.90 are indicators of good model fit in SEM/PLS analysis. The low SRMR, relatively high NFI, and the consistency across d_ ULS, d_ G, and chi-square support the conclusion that the model is acceptable and suitable for further analysis.



Picture 3. Bootstrapping Diagram

Source: SmartPLS4 data, 2025

The bootstrapping results confirm that all paths in the structural model exhibit significant effects. The high R^2 values for constructs Z and Y indicate that the model demonstrates strong predictive power. With the presence of both direct and indirect significant effects of variables X1 and X2 on Y through Z, it can be concluded that this model is empirically valid and supports the proposed theoretical hypotheses.

Table 15. Path Coefficient

	Original Sample (O)	Sample Mean (M)	Standard deviation (STDEV)	T-statistics (O/STDEV)	P-values
X1 → Y	0.397	0.405	0.079	5.028	0
X1 → Z	0.472	0.474	0.108	4.359	0
X2 → Y	0.253	0.261	0.076	3.345	0.001
X2 → Z	0.418	0.416	0.129	3.252	0.001
Z → Y	0.31	0.292	0.096	3.224	0.001

Source: SmartPLS4 data, 2025

Table 16. Path Coefficients Result

Hypothesis	Result	Description
X1 (Conventional Marketing) → Y (Commercial Vehicle Sales)	Accepted	Positive and significant
X1 (Conventional Marketing) → Z (Consumer Purchase Intention)	Accepted	Positive and significant
X2 (Digital Marketing) → Y (Commercial Vehicle Sales)	Accepted	Positive and significant
X2 (Digital Marketing) → Z (Consumer Purchase Intention)	Accepted	Positive and significant
Z (Consumer Purchase Intention) → Y (Commercial Vehicle Sales)	Accepted	Positive and significant

Source: SmartPLS4 data, 2025

Original Sample: 0.397 (significant at P-value < 0.001, T-value = 5.028). This indicates a positive and significant effect of variable X1 on Y. It reflects that any increase in X1 will directly increase the value of Y. Original Sample: 0.472 (significant at P-value < 0.001, T-value = 4.359). This shows a positive and significant effect of variable X1 on Z, indicating that X1 also strongly contributes to shaping the mediating variable Z. Original Sample: 0.253 (significant at P-value = 0.001, T-value = 3.345 or > 1.96). The effect is positive and significant, although weaker compared to the relationship between X1 → Y. Original Sample: 0.418 (significant at P-value = 0.001, T-value = 3.252). This result demonstrates that X2 also significantly contributes to shaping Z as a mediating variable.

Table 17. Total Indirect Effect

	Original Sample (O)	Sample Mean(M)	Standard deviation (STDEV)	T-statistics (O/STDEV)	P-values
X1 → Z → Y	0.146	0.140	0.059	2.492	0.013
X2 → Z → Y	0.130	0.119	0.052	2.488	0.013

Source: SmartPLS4 data, 2025

Table 18. Indirect Test Result

Hypothesis	Result	Description
X1 (Conventional Marketing) → Z (Consumer Purchase Intention) → Y (Commercial Vehicle Sales)	Accepted	Positive and Significant
X2 (Digital Marketing) → Z (Consumer Purchase Intention) → Y (Commercial Vehicle Sales)	Accepted	Positive and Significant

Source: SmartPLS4 data, 2025

The effect of X1 on Y through Z (X1 → Z → Y) shows an original sample value of 0.146, T-value = 2.492 (> 1.96), and p-value = 0.013 (< 0.05). This reflects that every one-unit increase in X1 increases Y by 0.146 units through the mediating role of Z. The T-value and p-value confirm that this effect is statistically significant at the 95% confidence level (Hair, 2017; Subhaktiyasa, (2024). The effect of X2 on Y through Z (X2 → Z → Y) yields an original sample value of 0.13, T-value = 2.488 (> 1.96), and p-value = 0.013 (< 0.05). This indicates that each one-unit increase in X2 increases Y by 0.13 units through the mediator Z. Although slightly weaker than the X1 mediation effect, the result remains statistically significant.

In PLS-SEM, indirect effects represent the mediation mechanism through which independent constructs influence dependent constructs via mediating constructs. In this case, Z functions as the mediator between X1 and X2 on Y. The analysis of 111 respondents using SmartPLS4 demonstrates that conventional marketing (X1) significantly influences commercial vehicle sales (Y) through consumer purchase intention (Z) as a mediator. The indirect effect value of 0.146 (T-value = 2.492, p-value = 0.013) confirms that the mediation hypothesis is accepted. According to Cohen (1988), an effect size of 0.146 falls within the small-to-medium

range, meaning that each one-unit increase in conventional marketing leads to a 0.146-unit increase in commercial vehicle sales through increased purchase intention. Hair et al. (2019) further explain that effect size (f^2) interpretation follows Cohen's (1988) guidelines, where $f^2 = 0.02$ indicates a small effect, $f^2 = 0.15$ a medium effect, and $f^2 = 0.35$ a large effect. Thus, the indirect effect of 0.146 approaches the medium category, suggesting practical significance and marketing implications. Nitzl et al., (2016) also emphasizes the importance of mediation analysis in PLS-SEM to understand variable mechanisms, where significant small-to-medium indirect effects suggest that the mediator (purchase intention) partially explains the impact of conventional marketing on vehicle sales. Within the Hino dealership context, this finding indicates that conventional strategies such as automotive exhibitions or sales force visits directly and indirectly shape customer purchase intention.

The analysis also confirms that digital marketing (X2) significantly affects commercial vehicle sales (Y) through consumer purchase intention (Z), with an original sample value of 0.13, T-value = 2.488 (> 1.96), and p-value = 0.013 (< 0.05). The p-value below 0.05 reflects that this relationship is statistically significant, meaning the hypothesis is accepted. This implies that the more effective digital marketing becomes, the higher consumer purchase intention will be, which in turn positively impacts commercial vehicle sales. These findings align with consumer behavior theory and the integrated marketing communications model, where digital marketing serves as an external stimulus influencing consumer attitudes and intentions before purchase decisions are made. Kotler & Armstrong, cited in Siregar, (2024), argue that purchase intention emerges after consumers receive stimuli from a product, leading to curiosity, trial, and eventually a desire to purchase. This reinforces the idea that digital marketing not only affects sales directly but also indirectly by increasing purchase intention as a preliminary step in the decision-making process (Kotler & Keller, 2016).

The results are consistent with prior studies. For example, Sari et al., (2024) found that digital marketing content significantly influenced purchase intention by 72.4% at Hyundai Gowa. Similarly, research on Tunas Jaya Mobilindo Showroom reported that digital marketing boosted annual vehicle sales growth by 62%. Furthermore, (Nirmala DS et al., 2024) emphasized that digital marketing significantly enhances purchase intention across digital platforms. These findings are also consistent with research in other automotive sectors, both motorcycles and cars, new and used demonstrating that digital marketing substantially increases sales volume.

V. Conclusion

Based on the research findings, both conventional and digital marketing strategies significantly contribute to increasing consumer purchase intention, which in turn drives the growth of commercial vehicle sales, including trucks and buses. Conventional marketing shows a stronger direct impact on sales, while digital marketing is effective in expanding market reach and enhancing consumer interaction through online media. Therefore, Hino dealers in the Greater Jakarta area (Jabodetabek) need to integrate these two strategies. Conventional marketing activities such as exhibitions, customer appreciation events, and direct promotions remain essential for building personal relationships and customer trust. Meanwhile, digital marketing must be maximized through the use of social media, websites, online advertising, and marketplace platforms to reach a broader consumer base and strengthen brand awareness. The role of purchase intention as a mediator highlights that marketing efforts should focus on enhancing customer experience and satisfaction, both offline and online, to effectively drive purchasing decisions.

Hino dealers in Jabodetabek are advised to implement several strategic steps to boost consumer purchase intention and increase sales. Practical recommendations include optimizing digital marketing through engaging and educational content on social media and digital platforms such as Facebook, Instagram, YouTube, TikTok, and similar channels, as well as strengthening direct sales programs with loyal customers through interactive events like gatherings that involve customers directly, alongside integrated training for the sales and marketing team. Additionally, leveraging digital data for consumer behavior analysis

is recommended. Collaboration with the Sole Brand Holder Agent (ATPM) and dealer networks is also considered essential to enhance service and marketing distribution.

It is further recommended to adopt an integrated marketing strategy that combines conventional approaches such as commercial vehicle exhibitions, direct consumer visits, and brochure distribution with digital strategies like social media campaigns and data-driven marketing (e.g., Meta Ads, Google Ads, TikTok Ads, and similar platforms), synergized to effectively reach a wider market segment. From an academic perspective, future research is suggested to explore other mediating variables such as customer loyalty or brand trust to deepen the understanding of the relationship between promotional strategies and sales outcomes, conduct comparative studies across different brands to assess the effectiveness of marketing strategies, and broaden the research scope by involving a larger number of respondents or audiences to ensure more representative and generalizable results.

References

- Adhawiyah, Y. R., & Anshori, M. I. (2019). Peran pemasaran media sosial dalam menciptakan keputusan pembelian melalui kesadaran merek (Studi pada Instagram Clothing Line Bangjo). *Jurnal Aplikasi Administrasi*, 22(1).
- Akbar, M. A. (2023). *Pengaruh strategi pemasaran terhadap keputusan pembelian mobil Mitsubishi Pajero* [Undergraduate thesis].
- Amalana, A. (2022). *Pengaruh promosi dan digital marketing terhadap keputusan pembelian melalui mediasi minat beli pada e-commerce Shopee* [Undergraduate thesis].
- Gaikindo. (2023). *Laporan penjualan kendaraan bermotor Indonesia tahun 2023*. <https://www.gaikindo.or.id/indonesian-automobile-industry-data/>
- Gaikindo. (2024). *Laporan penjualan kendaraan bermotor Indonesia tahun 2024*. <https://www.gaikindo.or.id/indonesian-automobile-industry-data/>
- Gaikindo. (2024, Desember 1). Penjualan mobil November 2024 turun, industri waspada. *Gaikindo*. <https://www.gaikindo.or.id/penjualan-mobil-november-2024-turun-industri-waspada/>
- Ghozali, I. (2016). *Aplikasi analisis multivariate dengan program IBM SPSS 23*. Badan Penerbit Universitas Diponegoro.
- Hair, J. F., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3). <https://doi.org/10.1016/j.rmal.2022.100027>
- Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, 109, 101–110. <https://doi.org/10.1016/j.jbusres.2019.11.069>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems*, 116(1), 2–20. <https://doi.org/10.1108/IMDS-09-2015-0382>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review*, 33(3), 405–431. <https://doi.org/10.1108/IMR-09-2014-0304>
- Heru, O., Rokhmawati, N., Kuncorowati, H., & Supardin, L. (2022). Pengaruh harga, iklan, dan citra merek terhadap minat beli Honda Scoopy di Yogyakarta. *Jurnal Ilmu Humaniora*, 11(1). <http://stp-mataram.e-journal.id/JIH>

- Khadiqi, D. F., Kusmayati, N. K., Kurniawan, Y., Kurniawan, T., & Wulansari, D. (2024). Analisa strategi pemasaran terhadap omset penjualan di dealer Yamaha Al-Handoko Motor. *TEKNOBIS: Teknologi Bisnis dan Pendidikan*, 2, 324–329.
- Kotler, P., & Keller, K. L. (2016). *Marketing management* (15th ed.). Pearson Education.
- Nirmala, D. S., Nafiqoh, A., & Manjasari, P. V. (2024). Pengaruh pemasaran digital terhadap minat beli konsumen (Studi pada PKM Tabaxain.aja). *EMBISS: Entrepreneurship, Management, Business, and Information Systems Studies*, 4(2). <https://embiss.com/index.php/embiss/article/view/287>
- Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems*, 116(9), 1849–1864. <https://doi.org/10.1108/IMDS-07-2015-0302>
- Oktaria, E. T., Zainab, & Helmita. (2024). Strategi promosi dalam meningkatkan volume penjualan mobil Ertiga pada PT Persada Lampung Raya Cabang Diponegoro di Bandar Lampung. *Jurnal Ekonomi dan Bisnis*, 5(1).
- Perdana, K. S., Sulistiowati, & Churniawan, A. D. (2020). Rancang bangun aplikasi dashboard pengunjung (Studi kasus pada Museum Teknoform Universitas Dinamika). *Jurnal Sistem Informasi dan Komputerisasi Administrasi (JSIKA)*, 9(4).
- Pramesti, G. (2023). *Analisis pengaruh promosi penjualan terhadap keputusan pembelian mobil Toyota Veloz melalui minat beli pelanggan sebagai variabel mediasi di Dealer Tunas Toyota Radin Inten* [Diploma thesis, Politeknik STMI Jakarta].
- Schiffman, L. G., & Kanuk, L. L. (2008). *Consumer behavior* (7th ed.). Pearson Education.
- Sari, E. P., Aras, R. A., & Sucipto, K. R. R. (2024). Analisis pengaruh konten digital marketing terhadap minat beli produk mobil Hyundai. *YUME: Journal of Management*, 7(1).
- Sayyida. (2023). Structural equation modeling (SEM) dengan SmartPLS dalam menyelesaikan permasalahan di bidang ekonomi. *Journal MISSY (Management and Business Strategy)*, 4(1).
- Shmueli, G., Ray, S., Manuel Velasquez Estrada, J., & Chatla, S. B. (2015). The elephant in the room: Evaluating the predictive performance of partial least squares (PLS) path models. *Social Science Research Network (SSRN)*. <http://ssrn.com/abstract=2659233>
- Siregar, A. I. (2024). Digital marketing dalam menghadapi persaingan bisnis di era digital: Kajian konseptual. *Jurnal Ilmiah Universitas Batanghari Jambi*, 24(3), 2921. <https://doi.org/10.33087/jiubj.v24i3.5678>
- Subhaktiyasa, P. G. (2024). PLS-SEM for multivariate analysis: A practical guide to educational research using SmartPLS. *EduLine: Journal of Education and Learning Innovation*, 4(3), 353–365. <https://doi.org/10.35877/454RI.eduline2861>
- Sugiyono. (2022). *Metode penelitian kuantitatif, kualitatif, dan R&D*. Alfabeta.
- Triyono, R., Mutia, Y. A., Gerhaen Purwansya, Y., Hidayati, N., Yustina, B., & Mutia, A. (2022). Strategi social-interactive marketing dalam rangka menciptakan brand awareness dan brand image produk mobil BEV (Battery Electric Vehicle) Indonesia. *Institut Pertanian Bogor Press*.