THE IMPACT OF E-COMMERCE ON DIGITAL FARMERS' VEGETABLE SALES IN JAKARTA METROPOLITAN AREA

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ABSTRACT

In recent years, e-commerce for fresh products, including fruits and vegetables, has rapidly grown in Indonesia, altering consumer behaviour and increasing agricultural producers' participation in the online market. This study examines factors influencing online vegetable sales growth, emphasizing e-commerce's transformative impact on the agricultural sector, especially in urban Indonesia. Focusing on online vegetable merchants in Jabodetabek (Jakarta Metropolitan Area), data was collected via an online survey on the Populix platform from March to August 2023 involving 120 merchants. Using logistic regression analysis, the study found that merchant age, supplier cooperation, user types, geographical regions, outlet types, and farmer collaboration significantly affect online vegetable sales. Younger merchants are more adaptive to technology, underscoring digital innovation's role in this sector. Direct cooperation with farmers enhances product quality and availability, while geographic location and outlet type influence sales reach and effectiveness. The study highlights the importance of understanding buyer demographics, strategic partnerships, and technology use in sales strategies. It implies that supporting young online vegetable merchants through digital innovation, strategic partnerships, and advanced technology is crucial for expanding their market and improving operational efficiency in agricultural e-commerce.

Key words: customer, e-commerce, fresh produce, logistic regression, partnership, vegetable traders

INTRODUCTION

The COVID-19 pandemic has spurred the growth of e-commerce, particularly in the fresh produce sector, (e.g., vegetables), leading to a more localized B2C (business to consumer) business model. This focus on local markets is crucial due to the perishable nature of vegetables (Du et al. 2020; Elik et al. 2019; Rajapaksha et al. 2021). Indonesia experienced a significant increase in interest in online vegetable shopping in 2022, with a 90% surge in Google searches in the first quarter (Annur 2022). This indicates a shift in consumer behavior due to the pandemic, in line with the consistent annual growth of the food and beverage packaging industry, including processed vegetables, which reached USD 40.11 billion in 2022. From an export perspective, Indonesia's vegetable exports declined in 2021 (Ahdiat 2023), with Taiwan remaining the largest export destination, followed by China and other Asian countries as the main export targets (Rizaty 2022).

In line with these changes, the role of aggregators in marketing agricultural produce has become increasingly crucial. The Ministry of Economic Affairs (2016) defines an aggregator as a marketer of agricultural products who leverages information and communication technology. Aggregators are entities or individuals who perform "aggregation", the process of collecting and combining products or services from various sources to strengthen market position and reach a broader consumer base (Kraus et al. 2021; Lu et al. 2020; Valarezo et al. 2021). Essentially, they gather smaller quantities of produce from different farmers and consolidate them into larger volumes for easier sale to markets or distributors. Aggregators can take various forms, including individuals, SMEs, cooperatives, state-owned enterprises, or private companies (Atmojo et al. 2023; Simamora and Sumarwan 2023). In the context of agricultural marketing, "aggregation" specifically refers to the process of the collection and combination of products or services from diverse sources to strengthen market position and reach more consumers (Abraham et al. 2022; Kilwinger and van Dam 2021; Tittonell et al. 2021). In the case of agricultural produce, this involves gathering products from various farmers to create a consistent and adequate supply that can meet market demand. Aggregators function as collectors or intermediaries, providing valuable services and products to farmers while maintaining relationships with marketing intermediaries (Tapasvi 2009). The digital era offers additional value to the agricultural chain, which aggregators can effectively utilize (Clercq et al. 2019).

In today's digital era, the agriculture sector and businesses face significant challenges, including high transaction costs (Smidt and Jokonya 2022), limited market access (Kubatko et al. 2022), and difficulties in effectively reaching customers (Ridaura et al. 2021). Modernizing operations with the latest technology is crucial to ensure business continuity. However, there often exists an information imbalance and barriers to leveraging information and communication technology (ICT), limiting the ability of farmers and small entrepreneurs to compete in the global market (Thongoh et al. 2021; van Campenhout 2022). Inefficiencies in resource management and distribution also hinder productivity growth and development. The complex and diverse issue of vegetable sales in urban areas encompasses the gap between producers and consumers, resulting in distribution inefficiencies and high logistics costs, detrimentally affecting farmers and consumers (Magalhães et al. 2021; Paciarotti and Torregiani 2021). The limitation of agricultural land near urban areas reduces the production of fresh local vegetables, necessitating the transportation of vegetables from distant areas, potentially lowering quality and nutritional value due to freshness issues (Giyarsih et al. 2023; O'Sullivan et al. 2019). In this context, the aggregation concept offers a crucial solution: utilizing ICT-based services to address these challenges (Ranjan 2017). Aggregation plays a role in reducing transaction costs and facilitating market access through digital platforms, which are vital for company modernization, enhancing network access, and advancing agricultural productivity and raw material supply for the processing industry. In this rapidly changing era, IT aggregators leveraging the access internet have seen rapid growth, especially in cities prioritizing speed, efficiency, and dynamism.

Before the pandemic, Romania preferred to use platforms like Facebook to sell local agricultural product innovations (Butu et al. 2020). A similar phenomenon also occurred in Indonesia, where vegetable traders utilized Facebook for the same purpose. Before the pandemic, the main focus was increasing production rather than diversifying online marketing platforms. However, the COVID-19 pandemic drove a significant shift towards diversifying online marketing channels, marking an evolution in business strategy and information technology. Aggregator businesses use the access internet in the form of social media and through more structured applications or websites to maximize the marketing and distribution potential of agricultural products (Jahroh and Meliala 2021). This marks a significant shift in how agricultural businesses respond to challenges and leverage opportunities in the digital era.

Marketing's primary function lies in connecting producers to consumers, particularly relevant for vegetables given their homogeneous nature with numerous sellers and buyers, leading to a stable market price (Beninger and Francis 2021; Kilwinger and van Dam 2021; Nordhagen et al. 2023). Although the Indonesian vegetable market exhibits characteristics of an oligopolistic market, in an oligopolistic market structure, each seller has significant influence over prices and market conditions, which is different from a highly competitive market where many sellers have little or no individual influence over the market (Hendricks and Mcafee 2010; Mulyana 2019). For example, Sayurbox is one of the aggregators in the context of the vegetable market in Indonesia (Jahroh and Meliala 2021). Online commodity-based aggregators offer robust sales information systems. This allows producers to set product prices dynamically (Lambert, 2012). This research is consistent with previous literature regarding the impact of e-commerce adoption on farmers' participation in digital financial markets in rural China (Su et al. 2021). Earlier studies were conducted on the introduction of rural and agricultural development in the digital era (Ma et al. 2023) and the influence of rural environment, capital, and farmer participation in e-commerce sales behavior (Li et al. 2021). However, this research offers a unique perspective by focusing on the digital farmer market in Indonesia's capital, an area often neglected in previous studies that primarily examine rural settings. Additionally, it explores specific trends in vegetable sales through e-commerce, unlike past research that uses broad, bivariate probit models to analyze e-commerce sales behavior. This study delves into the impact of e-commerce on the digital farmer market in Indonesia, particularly within an urban context and specifically regarding vegetable sales. This study sheds light on how digitalization affects the agricultural sector in an urban environment. This analysis highlights the differences between rural contexts and previous research focus on digital financial markets, further exploring the interaction between digital technology and traditional farmer market traditions. Ultimately, this research reveals valuable insights into local economic dynamics, supply chain management, and consumption patterns in the digital era.

With these considerations, this study sought to investigate the factors driving the rise in online vegetable sales. To identify these factors, a logistic model was employed to analyze data from a survey of online market traders who actively participated in e-commerce platforms. The impact of e-commerce on traders was measured based on the perceived percentage increase in vegetable sales by traders. The logistic regression analysis utilized two binary dependent variables (0 and 1) and independent variables in both numerical and dummy forms to estimate the factors contributing to this increase. The results of this study provided valuable insights into the interaction between e-commerce and digital marketing in the agriculture sector, ultimately contributing to the development and improvement of future digital marketing strategies.

MATERIALS AND METHODS

Location and time of research. The study was conducted using an online survey technique through the Populix platform, a paid consumer survey platform that facilitates connections between researchers from various industries and respondents across Indonesia. The target population for this research was online vegetable traders operating in the Jakarta, Bogor, Depok, Tangerang, and Bekasi (Jabodetabek) areas, sometimes referred to as Jakarta Metropolitan Area. This area was chosen as the research location because it is Indonesia's largest economic and trade centre, with a high population density, good infrastructure, and dynamic economic activities (Permanasari et al. 2024; Rustiadi et al. 2021). Additionally, the intense competition among traders, logistic and distribution issues due to severe traffic congestion, and challenges in maintaining product freshness during delivery make Jabodetabek an ideal region to study the dynamics of online vegetable trading, from opportunities to challenges faced by online vegetable traders. Data collection was done from March to August 2023.

Data collection and research instrument. This research recruited 120 online vegetable trader respondents, representing 20.68% of the total 580 traders, according to Populix's internal data. Based on Ghozali's (2013) recommendation of 20 respondents per independent variable, this study considered six parameters, thus requiring 120 respondents. A minimum % response rate of 10.20% is standard for online surveys (Zapata et al. 2016). In the analysis, the dependent variable was coded (1) for an increase in online sales exceeding 10.52%, representing the average sales increase reported by the 120 traders. Independent variables were coded (1) for partnering with more than six suppliers, users who understand the e-commerce system, regions with Jakarta warehouses, outlets with both conventional and online stores, and farmers who collaborate with farmers. Independent variables were coded (0) for partnering with ≤ 6 suppliers, users who do not understand e-commerce, warehouse regions in Botabek, outlets that are only online, and farmers without farmer collaboration. Additionally, age was analyzed as a continuous variable, not a category.

Analytical framework. Logistic regression is an important method in statistical analysis. It helps us understand and interpret the relationship between factors and dichotomous outcome variables. It shines in scenarios where results are binary.

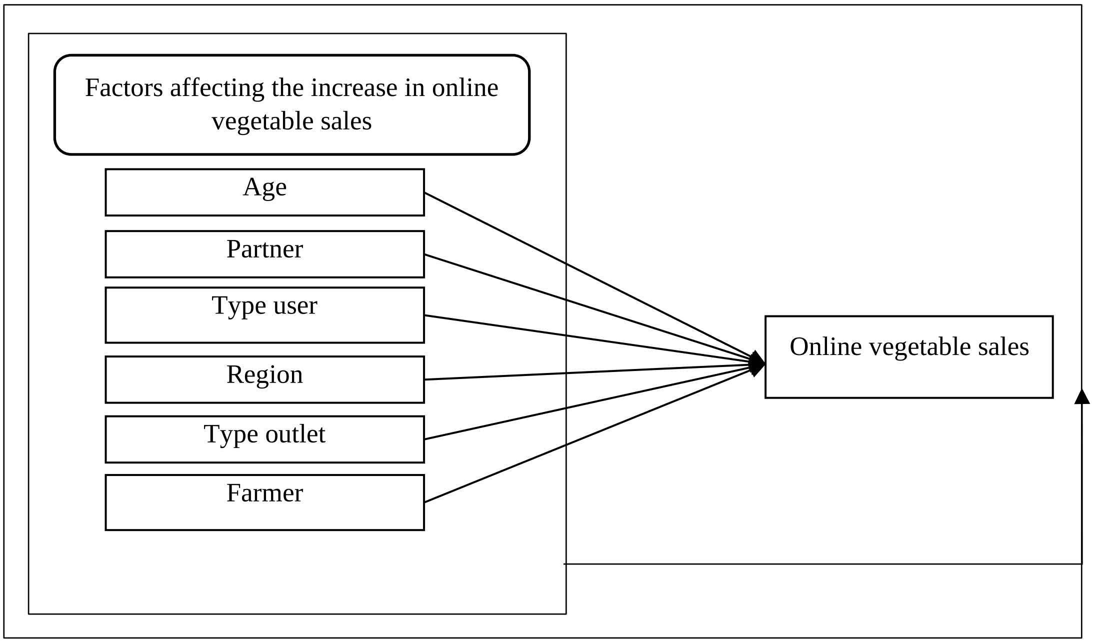

Figure 1. The conceptual framework.

Figure 1 illustrates the conceptual framework used in this study to identify factors influencing the increase in online vegetable sales. This framework aims to map out hypothesized variables that impact online sales, including age, partner, user type, region, outlet type, and farmer. By understanding how these factors interact and contribute to online vegetable sales, the study can more effectively analyze its findings. Table 1 provides a quick reference guide to the symbols and descriptions used in this analysis, helping you understand interactions and measurements in the models used in this research.

Table 1. Symbols used in equations

Symbol	***Description***
π(x)	Probability of the outcome given input x
AG	Age of the online trader
PR	Number of vegetable suppliers; 1 = >6 suppliers, 0 = ≤ 6 suppliers Suppliers are categorized into two groups based on the number of partners that traders have, namely ≤ 6 suppliers and > 6 suppliers, aims to identify the impact of partnerships on the increase in online vegetable sales in the Jabodetabek area. Using the number (0) for traders with six or fewer suppliers and the number (1) for traders with more than six suppliers provides a basis for in-depth statistical analysis. Data is classified based on these two categories to examine the relationship between the number of suppliers and the percentage increase in online vegetable sales. Statistical techniques like chi-square or logistic regression are used to determine if there is a significant relationship between the number of suppliers and sales increase. The percentage increase (Y) is also analyzed to assess the impact of partnerships on sales. The analysis results will be interpreted to determine if traders with more than six suppliers (category 1) show a significant increase in sales compared to those with ≤ 6 suppliers (category 0).
TU	Activity in using the e-commerce system; 1 = active, 0 = passive
RG	Company domicile region; 1 = Jakarta, 0 = other greater Jakarta areas including Bogor, Tangerang and Bekasi districts
TO	Type of outlet owned; 1 = conventional and online outlet, 0 = online outlet
FR	Traders who have cooperation with farmers; 1 = have cooperation, 0 = no cooperation
β0, β1, β2, ..., βp	Coefficients in the logistic regression model
x1, x2, ..., xp	Independent variables or predictors
g(x)	Logit function, the logarithm of the odds
Y	Dependent variable (Increase in vegetable sales as a percentage; 1 = Increase >10.52%, 0 = Increase <10.52%)
L_proposed	Likelihood of the proposed model
R^2_Logit	Pseudo R^2 in logistic regression
-2LL_Null	Negative twice the log-likelihood of the null model
-2LL_Model	Negative twice the log-likelihood of the proposed model
N	Sample size
Cox and Snell R^2	An adaptation of R^2 for logistic regression
Nagelkerke R^2	A modification of Cox and Snell R^2 that adjusts the scale to vary between 0 and 1

Note: This table outlines the symbols and descriptions used in logistic regression analysis, providing a concise reference for understanding the relationships and measurements within the model in this research.

Logistic regression is a specific form of discriminant analysis, in which the response variable has two categories: 0 and 1, and is predicted by a set of predictor variables (x) (Hosmer dan Lemeshow 2000). It assesses whether the probability of the dependent variable's occurrence can be predicted through independent variables. Researchers analyzed the data using SPSS software version 26. In essence, a logistic model estimates the probability or risk of an object. The logistic regression model equation is as follows:

$$\pi(x) = \frac{\exp\,(\beta_0 + \beta_1.x_1 + \cdots + \beta_p.x_p)}{1 + \exp\,(\beta_0 + \beta_1.x_1 + \cdots + \beta_p.x_p)} \tag{1}$$

Where p = number of predictor variables.

When transformed using the logit transformation, the equation becomes:

$$\mathrm{g(x)} = \mathrm{In}\left(\frac{\pi\,(\mathrm{x})}{1 - \pi\,(\mathrm{x})}\right) = \beta_0 + \beta_1.\mathrm{x}_1 + \cdots + \beta_\mathrm{p}.\mathrm{x}_\mathrm{p} \tag{2}$$

Logistic regression analysis estimates the relationship between the categorical response variable and predictor variables (Hosmer and Lemeshow 2000). There are different types of logistic regression, including binary, multinomial, and ordinal, depending on the number of categories in the response variable. This method is flexible in assumptions and remains robust even when assumptions for discriminant analysis are not met. The key difference from linear regression is that the dependent variable in logistic regression is categorical, while in linear regression, it is continuous (interval or ratio). Both methods serve as valuable tools for statistical prediction and exploration (Yamin 2021).

Hair et al. (2006) describe logistic regression as analogous to discriminant analysis in its objective: identifying independent variables that can classify the dependent variable's membership and establish a classification system based on a logistic model. The logistic regression model equation for analyzing the impact of e-commerce on repeat vegetable purchases is:

$$Y = \beta_0 + \beta_1 AGij + \beta_2 PRij + \beta_3 TUij + \beta_4 RGij + \beta_5 TOij + \beta_6 FRij \tag{3}$$

Hypothesis

H0 : $\beta1 = \beta2 = \ldots = \beta p = 0$, which states that the independent variables have no significant effect on the dependent variable, namely the increase in the percentage of online vegetable sales.

H1 : At least one $\beta i \neq 0$ (i = 1, 2, ..., p), which states that at least one independent variable has a significant effect on the increase in the percentage of online vegetable sales.

Hypotheses in this study are based on the logistic model designed for evaluating MarketMaker, where field conditions face limited data about factors influencing e-commerce use and impact in agriculture (dependent factors) (Zapata et al. 2016). The focus is on farmer market sales due to MarketMaker, influenced by inputs, activities, and outputs.

Both logistic and multiple linear regression are sensitive to high correlations among independent variables (necessitating multicollinearity checks) (Tabachnick and Fidell 2013),. Therefore, measures like VIF, tolerance, or correlation levels can be used to detect multicollinearity among independent variables. Outlier examination can affect the identification of model classification errors and reduce model goodness of fit.

The overall model test is conducted using the G test or log-likelihood ratio test (-2Log L), which compares the log-likelihood of the proposed model (-2Log LProposed) with that of the base/null model (-2Log LNull). The log likelihood ratio test follows a chi-square distribution with p degrees of freedom for the independent variables and a specific α, e.g., 5%. The testing process is as follows:

Hypotheses

H_0: $\beta1 = \beta2 = \ldots = \beta p = 0$

H_1: At least one $\beta i \neq 0$, i = 1, 2, ..., p

Testing statistics for the log likelihood ratio test or G test follows a chi-square distribution with p degrees of freedom and α = 5%.

$$G = -2In\left(\frac{L_{proposed}}{L_{proposed}}\right) \quad (4)$$

The decision criterion is to reject H_0 if the chi-square p-value is less than α = 5%. This test aims to reject H_0, indicating that including independent variables in the model significantly influences the explanation or prediction of success or failure in the dependent variable's outcome. This result also can also interpret the ability of all independent variables in the model to predict the dependent variable's outcome. Similar to the Likelihood Ratio Test, the Hosmer and Lemeshow Test (H-L statistic) can also be used. This test divides participants into several classes based on the model's predicted probabilities and then calculates a chi-square value from observed and expected frequencies. Suppose the Hosmer and Lemeshow (H-L statistic) is less than or equal to 0.05, the null hypothesis is rejected, indicating significant differences between the model and its observations, and suggesting poor model fit. Conversely, a Hosmer and Lemeshow (H-L statistic) value greater than 0.05 suggests the model can predict observed values or is acceptable due to its fit with observed data.

Following the overall model test, the significance of each independent variable's regression coefficient on the dependent variable using the Wald statistic was examined.

Hypotheses

H_0: βi = 0
H_1: βi ≠ 0, for i = 1,2,…,p

The Wald test following a chi-square distribution, serves as the testing statistic. With α = 5%, the null hypothesis (H_0, assuming no significant relationship between independent and dependent variables) is rejected if the chi-square p-value is lower than 0.05. Assessing the model's goodness of fit in logistic regression involves two measures: Pseudo R Square, analogous to R Square, in linear regression) and prediction accuracy (also known as Hit Ratio). The calculation of Pseudo R Square:

$$\mathrm{R}^2{}_{Logit} = \frac{-2LL_{Null} - (-2LL_{Model})}{-2LL_{Null}} \quad (5)$$

Another measure developed with a similar meaning is Cox and Snell R Square, calculated as:

$$\mathrm{R}^2 = 1 - \left(\frac{-2LL_{Null}}{-2LL_{proposed}}\right)^{\frac{2}{n}} \quad (6)$$

Cox and Snell R Square and Nagelkerke R-squared are measures of model fit used in logistic regression, similar to R-squared in multiple linear regression. However, they are based on likelihood estimation techniques and have different properties.

$$\mathrm{R}^2 = \left(\frac{1 - \left(\frac{-2LL_{Null}}{-2LL_{proposed}}\right)^{\frac{2}{n}}}{1 - (-2LL_{Null})^{\frac{2}{n}}}\right) \quad (7)$$

These measures like R^2 indicate the model's ability to account for variation. A perfect model fit would have R^2 equal to 1, while a value of 0 indicates poor fit. In addition, SPSS provides prediction accuracy in the classification table. This measure, calculated from correctly predicted data points, should ideally approach 100% for optimal accuracy.

RESULTS AND DISCUSSION

Characteristics of farmers. Logistic regression analysis is a highly useful statistical method for modeling the relationship between independent variables and a dependent variable, especially when the dependent variable consists of categorical data (Yamin 2021). In this study, two main characteristics for each variable influencing sales success were investigated. These characteristics divided traders into two groups based on certain conditions or criteria, providing insights into factors that may affect the increase in online vegetable sales. First, the variable of collaboration with farmers, where traders were divided into two groups. The first group consisted of 57 traders who partnered with farmers, while the second group comprised 63 traders without such partnerships. This highlights the importance of collaboration with farmers in their business dynamics. Second, the ability to use e-commerce systems emerged as another important variable. Here, 48 traders were categorized as active and capable of operating e-commerce systems effectively, while 60 traders were categorized as inactive or less capable. Third, warehouse location also became a determining factor, with 60 traders having warehouses in Jakarta and 60 others in Botabek (Bogor, Tangerang, Bekasi). These warehouse locations illustrate the logistical and distribution differences among traders. Fourth, the business model of online vegetable traders was divided into two groups: 57 traders operated both online and conventional stores, while 63 traders operated exclusively online. This demonstrates the diverse sales strategies among traders. Fifth, partnership relationships with suppliers were the final variable, with 61 traders having partnerships with their suppliers, while 59 others did not. These relationships can affect the ease of access to product supplies. The study also noted that online vegetable traders ranged in age from 19 to 52 years, with an average age of 27 years. Considering all these characteristics, online vegetable traders were able to increase their sales by 10.52%, with an overall classification accuracy reaching 95.80%, thus emphasizing the importance of these factors in online sales success. The classification accuracy of the increase in the percentage of vegetables sales is 95.80% (Table 2).

Table 2 shows the observation of the increase in percentage of vegetable sales based on the classification of the number of suppliers. From the total observations, it is evident that 66 traders with six or fewer suppliers (classification 0) did not experience an increase in vegetable sales percentage, while only 2 traders in this category experienced an increase. On the other hand, among traders with more than six suppliers (classification 1), 3 traders did not experience an increase, whereas 49 traders experienced an increase in the percentage of vegetable sales. Thus, the total increase percentage for both categories is 95.80%. This data indicates that traders with more than six suppliers tend to experience a higher increase in the percentage of vegetable sales compared to traders with six or fewer suppliers.

Table 2. Observation of the increase in percent vegetable sales (Y).

Observation	Classification	Increase in percent sales of vegetables (Y)		Percent of correctly predicted increase in vegetable sales
		0	**1**	
Increase in percent sales of vegetables (Y)	0.00	66	2	97.10
	1.00	3	49	94.20
Total percent				95.80

There is a significant increase in vegetable sales revenue from 2021-2022 to 2022-2023, based on the analysis of 120 traders (Table 3). Total sales increased from Rp1,324,000,000 to Rp4,569,000,000, with vegetable sales revenue rising from Rp1,480,525,000 to Rp1,745,658,000. The percentage increase in vegetable sales from total sales reached 10.52%. The average annual vegetable sales also increased, from Rp18,506,562 to Rp21,820,725. Thus, the significant increase in vegetable sales revenue, as seen in the rise of total sales and the percentage increase in vegetable sales, reflects strong growth in the vegetable sales sector.

Table 3. Revenue and percentage increase in vegetable sales.

	Sales revenue (Rp million per trader)		**Vegetable revenue (Rp million per trader)**		**Percentage increase in sales of traders**	**Percent increase from total sales**
	2021-2022	2022-2023	2021-2022	2022-2023		
Total sales	1,324.00	4,569.00	1,480.52	1,745.65		
Average sales	110.33	169.22	18.50	21.82		
Minimum sales	35.00	36.00	1.50	1.68	1262.92%	10.52%
Maximum sales	370.00	955.50	128.00	181.54		

Note: Analysis results from 120 traders

Assumptions of logistic regression. The multivariate analysis revealed a low level of multicollinearity, with all correlations between independent variables exceeding 0.90, indicating no significant multicollinearity concerns in the model. In this research context, the set standard deviation value should not exceed 3. Based on this, no observations with a standard deviation above this value were found, eliminating the possibility of outliers in the data. The -2 log-likelihood test comprises two steps: a null model without independent variables and a proposed model with both dependent and independent variables.

Table 4. - 2 Log Likelihood test

Step	**-2 Log likelihood**	**Cox and Snell R Square**	**Nagelkerke R Square**
1	37.28[a]	0.65	0.88

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

The results revealed a significant decrease in the -2 log-likelihood value, dropping from 164.22 in the null model to 37.28 in the proposed model. This substantial decrease indicates that the logistic regression model is suitable for the data and likely effective. To formally assess this improvement, the G-test is conducted. It compares the difference in the -2 log-likelihood values between the two models and calculates a chi-square statistic using the following formula:

$$x^2 = 164.22 – 37.28 = 126.94$$

This sizeable difference in -2 log-likelihoods (164.22 to 37.29) translates to a chi-square value of 126.94. Table 4 presents the detailed calculation of this specific value.

In the Omnibus tests, the chi-square value is 126.94, with six degrees of freedom indicating a highly significant model (p = 0.00) (Table 5). This confirms that the six independent variables, including age, partner, type of user, region, type of outlet, and farmer, collectively have a statistically significant influence on the dependent variable: the increase in the percentage of online vegetable sales.

The Pseudo R^2 logistic coefficient of determination was calculated as follows:

$$R^2 logit = \frac{164.22 - 37.28}{164.22} = 0.773$$

Table 5. Omnibus tests of model coefficients

		Chi-square	Df	Sig.
Step 1	*Step*	126.94	6	0.00
	Block	126.94	6	0.00
	Model	126.94	6	0.00

This calculation resulted in a Pseudo R^2 value of 0.77, indicating that 77.30 percent of the variation in the increase in online vegetable sales is explained by the model, including variables like age, partner, type of user, region, type of outlet, and farmer. Similar measures like Cox and Snell R2 (0.65) and Nagelkerke's R2 (0.88) offer alternative interpretations. Combined, these three measures suggest that between 65% and 88% of the variation in the increase in online vegetable sales can be explained by the included variables, with the remaining 12-35% due to other factors outside the model. This implies that the model demonstrates a strong influence of the independent variables on the dependent variable.

The Hosmer and Lemeshow test yielded a chi-square value of 9.47 and a significance level of 0.30 in Table 6. A significance level above 0.05 indicates no significant difference between the model's predictions and the observed data. Therefore, this result suggests that the logistic regression model is statistically valid and generally aligns with the observed values. While this doesn't necessarily imply perfect prediction, it means the model's overall fit is acceptable.

A classification matrix approach, specifically hit ratio analysis, was used to measure the level of prediction and classification of group members. Focusing on predicting the increase in online vegetable sales, the hit ratio analysis revealed the following: For participants categorized as experiencing an increase in vegetable sales percentage (less than or equal to 10.52%, coded as 0): there were 66 participants. Of these, 2 were correctly classified, resulting in a 97.10% accuracy rate. Meanwhile, for participants categorized as not experiencing an increase in vegetable sales percentage (greater than 10.52%, coded as 1): there were 3 participants. Of these, 49 were correctly classified, resulting in a 94.2% accuracy rate.

Table 6. Hosmer and Lemeshow test

Step	Chi-square	df	Sig.
1	9.47	8	0.30

Analysis results. Similar to the t-test in linear regression, the Wald test in logistic regression assesses the statistical significance of independent variables like age, partner, type of user, region, type of outlet, and farmer on the dependent variable: the increase in the percentage of online vegetable sales (Table 7). In general, a positive original coefficient in the "Variables in the Equation" table indicates a higher probability of the model predicting an increase in the dependent variable, while a negative coefficient reflects a lower probability of the model predicting an increase in the dependent variable, while a negative coefficient reflects a lower probability.

A constant value (α) of 1.33 indicates a general tendency towards an increase in the parameters studied, namely age, partnership, user type, region, outlet type, and farmer approach, assuming no other factors influence. However, for age, the coefficient is -0.02, indicating a negative relationship with the dependent variable, which is the percentage increase in online vegetable sales. This means that as online vegetable sellers age, they are less likely to achieve a more than 10.52% increase in online vegetable sales. This suggests that younger merchants, who are more skilled with digital technology and e-commerce, are more likely to realize a significant increase in online sales. The value of 10.52% comes from the average sales increase reported by 120 merchants who were part of the study. Thus, 10.52% is a benchmark for categorizing sales increases and is not directly caused by the age factor alone.

Table 7. Wald test variables in the equation

		B	S.E.	Wald	df	Sig.	Exp (B)
Step 1[a]	Age	-0.02	0.10	4.36	1	0.04	0.81
	Partner	-2.16	0.97	4.95	1	0.03	0.12
	Type user	1.87	1.00	3.49	1	0.06	6.49
	Region	2.03	1.19	2.93	1	0.09	7.62
	Type outlet	2.49	1.00	6.14	1	0.01	12.06
	Farmer	2.03	0.95	4.62	1	0.03	7.64
	Constant	1.33	3.12	0.18	1	0.67	3.78

Notes: Variable(s) entered on step 1: Age, Partner, Type user, Region, Type Outlet, Farmer

The original coefficient for the partner variable is -2.16, with a Wald value of 4.95 and a significance level of 0.26, indicating a negative relationship with the probability prediction when the original coefficient is negative. A lower partner coefficient value diminishes the predictive probability, indicating that each additional partner decreases the likelihood of achieving more than a 10.52% increase in online vegetable sales. The type user variable has an original coefficient of 1.87 and a Wald value of 3.49 at a significance level of 0.06. A positive coefficient value predicts a positive relationship between the independent variable and the probability prediction. Thus, each increase in the type of user raises the probability of accepting an increase in online vegetable sales by > 10.52%.

The region variable has an original coefficient of 2.03 and a Wald value of 2.93 with ($p = 0.09$). This indicates a positive relationship with the probability of accepting an increase in online vegetable sales by > 10.52%. In simpler terms, traders located in Jakarta (represented by 1 in the variable) are more likely to experience the mentioned sales increase compared to those in other regions. Similarly, the type outlet variable with a coefficient of 2.49 and a Wald value of 6.14 ($p = 0.01$) suggests a statistically significant positive relationship with the desired sales increase. This implies that owning both conventional and online outlets (represented by 1) increases the probability of achieving sales growth compared to solely online outlets.

Finally, the farmer variable with a coefficient of 2.03 and a Wald value of 4.62 ($p = 0.03$) demonstrates a positive association with the sales increase. Each unit increase in the variable (likely indicating closer cooperation with farmers) suggests a higher probability of experiencing the desired sales growth.

Determinants of the vegetable sales in the Jabodetabek area

Based on the results of the Wald test, the obtained logistic regression model is:

$$Log\frac{PS}{1-\mathrm{PS}} = 1.33 - 0.215\mathrm{AG} - 2.157\mathrm{PR} + 1.870\mathrm{TU} + 2.03\mathrm{RG} + 2.49\mathrm{TO} + 2.03\mathrm{FR}$$

Impact of trader's age. The variable 'age' showed a Wald value of 4.36 and a significance of 0.037 from the hypothesis testing results. From these results, it is evident that the significance of the 'age' variable is less than 5 percent (0.00 < 0.05), and the original coefficient is negative, rejecting H_0. This means 'age' has a positive and significant impact on the percentage increase in online vegetable sales. This hypothesis indicates that the higher the age of online vegetable traders, the more likely they are to decrease the percentage increase in online vegetable sales (10.52 percent). The study shows that as online vegetable traders age, the gains from increasing online vegetable sales decrease, necessitating younger traders with an average age of about 27 years.

Individuals aged 20-30 years are categorized as digital natives, defined as a generation born and living in the digital or internet age (Prensky 2001). Younger traders are more successful in the long run and achieve success faster if digital platform administrators provide support. Younger age accelerates the adaptation process to internet technology compared to older users (Domínguez and Rivera 2020; Giamalaki and Kolokotsa 2019). This is consistent with earlier studies that found a negative correlation between age and smartphone technology adoption (Michels and Musshoff 2022). Furthermore, younger farmers are more inclined to use digital innovations in agriculture (Tamirat et al. 2018). This age factor influences the ability to increase the percentage of online vegetable sales. Previous studies showed that the age of farmer market managers, used as a proxy for technical skill level, indicates that younger managers are more technologically skilled and can better utilize market makers (Zapata et al. 2016). Each increase in age negatively correlates with increased sales percentage, indicating that aging does not enhance sales due to less proficiency in digital technology marketing through e-commerce.

Impact of partnership. The 'partner' variable displayed a Wald value of 4.95 with a significance level of 0.03 (0.03 < 0.05). As the original coefficient is negative, the null hypothesis (H_0) is accepted. This indicates that the 'partner' variable has a negative and significant partial effect on the increase in online vegetable sales. 'Partner' refers to traders partnering with suppliers, including middlemen or farmers. Forming partnerships with at least six suppliers can increase online vegetable sales compared to working with more than six suppliers, both with farmers and middlemen. This impacts the marketing chain, making it effective to partner with only 1-6 people. A manager from KMM Dompet Dhuafa emphasized the importance of collaborating with 3-5 suppliers or producers to maintain a steady stock of a single agricultural commodity, reducing the risks of seasonal vegetable products. Seasonal products can cause farmer prices to drop, and in this situation, online vegetable traders can switch to major suppliers in Pasar Kramat Jati. These suppliers tend to buy products from farmers experiencing unstable seasonal harvests. Empirical research showed that for salad producers in modern markets in Ambon City, five suppliers and six producers for pakcoy are needed, with cooperation starting in 2017 (Suyono et al. 2023). Only 20% of traders partnered with middlemen, primarily from Jakarta and Tangerang, including Pasar Cipondoh, Pasar Rebo, and Pasar Kramat Jati. In comparison, the remaining 80% are direct farmers from areas like Cisarua Bogor, Cianjur, Sukabumi, Brebes, Lembang-Bandung, and Garut. Generally, these suppliers or vendors function as sellers of raw food resources to online vegetable traders for processing into specific products or services.

Impact of user type. This study found that the 'type user' variable had a Wald value of 3.49 and a significance level of 0.06. Since this significance value is less than the set threshold of 10% (0.06 < 0.10), H_0 is accepted. This indicates that 'type user' has a significant positive impact on the increase in online vegetable sales. Specifically, active users who understand the e-commerce system significantly contribute to sales increases. The results highlighted the importance of business owners' understanding and activity in using e-commerce systems, including routinely checking and updating their profiles in the marketplace. The online vegetable sales process is similar to physical store sales. The difference lies in the trader's activity in monitoring the app for orders, selecting vegetables, and the payment process directly entering the bank account. An earlier study determined that farmer markets that have participated longer in MarketMaker achieve higher sales increases than newcomers. This demonstrated MarketMaker's effectiveness in enhancing existing capacities (Zapata et al. 2016). The study also found that MarketMaker users who spent an average of 31 minutes per day monitoring the e-commerce system experienced sales increases. This conclusion is consistent with findings that showed user types (farmers acting as managers) who are active in MarketMaker and spend more than 30 minutes a month on their activities on the platform experience a sales increase of 3.78% compared to passive users (Zapata et al. 2016).

Impact of region. Based on the partial test results on the "region" variable, a Wald value of 2.93 with a significance level of 0.09 and a positive coefficient was found, thus rejecting the null hypothesis (H_0). This shows that the 'region' variable has a positive and significant effect on the increase in online vegetable sales percentage. The study indicates that more shipping warehouses in Jakarta lead to higher increases in online vegetable sales. This is due to the high market concentration among urban consumers in Jakarta who have a healthy and practical lifestyle in shopping for vegetables online. Research by Rakasyifa and Mukti (2020) found that Personal and psychological factors significantly influence the decision to buy vegetables and fruits online in Jakarta. These factors include personality, occupation, age, life stage, economic situation, and lifestyle. Jakarta's health-conscious population consuming vegetables is an example of a healthy lifestyle supported by online retail purchases. According to Shelbiana and Trimo (2022), by adopting technology safely, businesses like vegetable companies and Go-Pay can meet consumer needs and desires. Through agricultural e-commerce applications, consumers can easily order daily needs like vegetables. Digital payments facilitate transactions and support local farmers by buying vegetables from their farms, thanks to Go-Pay's collaboration with agricultural e-commerce platforms. Jakarta, as the city with the most e-commerce transactions, utilizes the Gojek app and its Go-Mart feature, offering over 130 types of fresh vegetables and fruits in collaboration with agricultural e-commerce to facilitate daily orders from home and payments through Go-Pay, reducing physical contact. As in the United States, the potential of large cities in creating agricultural e-commerce markets and the long-term success of farmer markets heavily depend on consumer support and presence. In this context, access to demographic and geocode data about consumer income and food preferences, as available through MarketMaker, can help determine the best marketing locations, as seen in states like Arkansas and Colorado (Zapata et al. 2016).

Impact of outlet type. Testing showed that the "type outlet" variable had a Wald value of 3.49 and a significance of 0.01. This result indicates that the variable is significant, with significance less than 5 percent (0.01 < 0.05) and a positive coefficient, thus rejecting the null hypothesis (H_0). Therefore, "type outlet" has a positive and significant effect on the increase in online vegetable sales percentage. The transformation of vegetable sales from conventional stores to e-commerce indicates that traders with both conventional and online outlets can increase revenue and the percentage of online sales. This is due to the expansion of the sales scope and the convenience of transactions for customers. Online vegetable traders also find e-commerce easy to operate, following the change in the digital era. Additionally, the use of wifi by online vegetable sellers aims to save costs and facilitate e-commerce operations. The type of online store alone does not affect the total sales of certain vegetables (Khairani et al. 2022). Therefore, the type of store can be a weakness for online traders in formulating sales strategies for fruits and vegetables on digital platforms, especially in Bogor City. In the new normal situation, online vegetable traders are advised to have conventional stores to tackle the risks of availability, distribution, and limited online selling time. Buyers tend to choose traditional markets in the new normal, making e-commerce less popular. Online, operational limitations also make it difficult for traders to maximize income from online vegetable sales. Field data shows that traders with only online stalls increase the percentage of their online sales by an average of 8.29 percent, below 10.52 percent.

Impact of farmers. Partial testing on the “farmer” variable yielded a Wald value of 4.61 with a significance of 0.03. It has a positive original coefficient, while the null hypothesis (H_0) is rejected. This finding indicates that the 'farmer' variable positively and significantly impacts the increase in online vegetable sales. This is reflected in the fact that most online vegetable traders collaborate directly with farmers rather than middlemen. This collaboration offers benefits, including a reduced supply chain, lower selling prices, fresher vegetables, more diverse and adequate vegetable supplies, and ease of distribution. It also helps farmers market their produce. About 80% of online vegetable traders get their supply directly from farmers, especially from Java regions like West Java, Central Java, and East Java. This finding aligns with research by Khairani et al. (2022), which mentions that online vegetable traders can collaborate in a reseller or drop shipper system with farmers, shortening the marketing chain from farmers directly to customers. This strategy maintains product freshness and ensures the best quality vegetables for customers, increasing positive reviews from customers.

Factors influencing the increase in online vegetable sales. Based on the results of simultaneous (together) statistical regression testing, the chi-square value is 126.94 with a degree of freedom of 6. At the same time, the significance level is less than 5 percent ($0.00 < 0.05$). Therefore, it can be concluded that Ho is rejected, meaning the variables age, partner, type user, region, type outlet, and farmer simultaneously (together) have a significant impact on the percentage increase in online vegetable sales (H_07: $\beta1 = \beta2 = \beta3 = \beta4 = \beta5 = \beta6 \neq 0$). From these results, it is concluded that the variables age, partner, type user, region, type outlet, and farmer simultaneously (together) and significantly influence the percentage increase in online vegetable sales at a significance level of $\alpha = 5$ percent and 10 percent.

This finding opens new insights into the factors influencing online vegetable sales. First, the age variable (age) indicates that buyer demographics play an important role in influencing purchasing behavior. This could include specific generational preferences for online purchases or their familiarity level with technology. Second, the presence of effective partners, including suppliers or online marketing platforms, can expand market reach and service reliability, ultimately affecting sales. Third, the user type (type user) provides insights into different market segments and how their needs and behaviors affect online vegetable buying. This could relate to differences between end-users (consumers) and business buyers (like restaurants or hotels). Fourth, the region factor (region) highlights the importance of localization in marketing and distribution strategies, considering differences in consumer accessibility and preferences in various regions. Fifth, the outlet type plays a crucial role in determining how vegetables are sold and marketed. This could relate to differences between direct-to-consumer (B2C) sales and business to business (B2B) sales. Lastly, the role of farmers (farmers) is not only crucial in the supply chain but also in ensuring the quality and sustainability of the products sold. Farmer involvement in marketing processes and distribution decisions can increase consumer trust and product image. By understanding the complex relationships between these factors, businesses can develop more effective strategies to increase online vegetable sales. These strategies include developing more user-friendly online platforms, strategic partnerships with various parties and targeted marketing campaigns for different market segments.

In addition, the understanding of the specific needs of various regions can help design more efficient logistics services and target more effective promotions. This research provides significant insights for businesses in the online vegetable sales industry and contributes to the academic literature on consumer buying behaviour and digital marketing. It shows that a holistic approach to understanding the various factors influencing buying behaviour can significantly increase sales and customer satisfaction. Although this research does not directly measure profitability, increasing sales can be an early indicator of e-commerce success. Increased sales only sometimes correlate with increased profits due to marketing and operational costs. However, in digital transformation and e-commerce, increased sales are an important early indicator of consumer's and producers' successful adoption of digital platforms (Falk and Hagsten 2015). The research data shows an increase in online vegetable sales by approximately 10.52% of total sales. Although the contribution of vegetables to total sales may seem small, this figure reflects a significant shift in consumer behaviour. This change is important, especially considering kitchen staples and meat still dominate most consumer purchases. Everett Rogers' Diffusion of Innovations theory supports this understanding, where the adoption of new technology (in this case, e-commerce platforms) follows a diffusion pattern that can be measured through early indicators like increased sales. Innovation adoption goes through certain stages, from knowledge to confirmation, and increased sales can be seen as part of this adoption process (Rogers 2003). Thus, this research not only evaluates the factors influencing online vegetable sales but also provides insights into how digital platforms are adopted and integrated into consumer shopping behaviour, which can ultimately impact the sustainability of the digital agricultural sector.

CONCLUSION

This study showed that age of the vendor, partnerships with suppliers, types of users, regions, types of outlets, and collaborations with farmers influenced significantly the increase in online vegetable sales. Younger merchants tended to be more adaptive to technology, highlighting the importance of digital innovation in this sector. Direct cooperation with farmers proved to enhance the quality and availability of products, while geographical location and type of outlet affected the reach and effectiveness of sales. Policymakers and e-commerce developers and should prioritize support for younger online vegetable traders, optimize partnerships with an effective number of suppliers, and leverage digital technology to expand market reach and enhance logistics efficiency, taking into account factors including age, user type, region, store type, and collaboration with farmers, to maximize the increase in sustainable online vegetable sales. For future research, it is suggested that the impact of new technologies and the integration of more innovative digital payment systems be explored to improve customer experience and operational efficiency in agricultural e-commerce. In additional, measuring costs and profit margins is crucial profitability. However, accurate cost data makes direct profitability analysis difficult in this study. Therefore, another limitation of this research is the unavailability of profitability data, suggesting that future research delve deeper into analyzing costs and profit margins in online vegetable e-commerce.

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