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DYNAMIC RELATIONSHIPS: E-COMMERCE SALES AND KEY EXOGENOUS VARIABLES IN THE PHILIPPINES

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Abstract:
This study delves into the complex and evolving landscape of e-commerce in the Philippines, focusing on the relationship between E-Commerce Sales as the endogenous variable and a set of influential exogenous variables, including Digital Marketing Spending, GDP Growth, Internet Penetration, and Mobile Phone Ownership. This research employs a flexible spline modeling approach, uncovers non-linear associations, and offers significant implications for academic understanding and practical applications. The findings underscore the growing impact of Digital Marketing Spending on E-Commerce Sales, revealing the paramount role of online advertising and promotional strategies in the digital marketplace. Moreover, the study explains the intricate interplay between GDP Growth, Internet Penetration, Mobile Phone Ownership, and E-Commerce Sales, highlighting the non-linear nature of these relationships. As the Philippines continues its economic expansion and technological integration, these associations exhibit insightful implications for policymakers, businesses, and e-commerce stakeholders.

Keywords: e-commerce sales, spline modeling, the Philippines

1. Introduction

The Philippines is a fast-growing e-commerce market in Southeast Asia, with a projected revenue of US$25.5 billion by 2027. The COVID-19 pandemic has increased the demand for online shopping as more Filipinos work and study from home (eCommerce, 25 July 2022). The top e-commerce platforms in the Philippines are Shopee, Lazada, Zalora, and BeautyMNL, and the most popular product categories include beauty, electronics, fashion, furniture, health, and household care (Tayao-Juego, 3 April 2020). However, e-commerce growth in the Philippines also faces challenges, such as low internet speed,

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inadequate infrastructure, low credit card penetration, and weak cybersecurity protection (Schia, 2018). The Philippine government has issued laws and policies to support the e-commerce industry, such as the Electronic Commerce Act (RA 8792) and the E-Commerce Philippines Roadmap (Clarete, 2019). However, more efforts are needed to address the gaps and barriers in the digital economy.

Various factors, such as digital marketing spending, GDP growth, internet penetration, and mobile phone ownership, influence E-commerce sales in the Philippines. The digital advertising market in the Philippines is expected to grow at a CAGR of 10.8% from 2021 to 2025, reaching US$1.2 billion by 2025 (Statista, July 2023). Digital marketing helps e-commerce businesses get more customers, increase brand awareness, and drive sales conversions (Balinbin, 26 August 2021). The Philippines' GDP grow by 7.2% in 2022 and is predicted to grow by 6.0% in 2023 after contracting by 9.6% in 2020 due to the COVID-19 pandemic (Highlights, 14 June 2023). GDP growth reflects consumers' economic activity and purchasing power, which can affect their demand for online goods and services (Dynan & Sheiner, 2018). The internet penetration rate in the Philippines was 67% in 2020, with about 73 million internet users expected to increase to 74% by 2025, with about 86 million internet users (Statista, July 2023). Internet penetration is critical for e-commerce development, enabling more people to access online platforms and services (Buhalis, D., & Deimezi, 2003). The number of smartphone users in the Philippines was estimated at 40.3 million in 2020, accounting for 36.8% of the population, and is projected to increase to 58.7 million by 2025, accounting for 53.7% of the population (CR Team, 30 October 2023). Mobile phone ownership is another important factor for e-commerce growth, as it allows consumers to shop online anytime and anywhere using their devices (Sandhu, 2012). Therefore, these factors likely influence e-commerce sales in the Philippines, as they shape the online behavior and preferences of consumers and businesses. These factors are considered when analyzing the e-commerce market in the Philippines.

Predicting e-commerce sales in the Philippines is essential for several reasons. It helps businesses plan strategies and optimize their operations based on market trends and customer behavior (Jeong et al., 2022). At the same time, it helps customers find the best deals and products that suit their needs and preferences (Zhao et al., 2019, November). It allows the government to monitor and regulate the e-commerce industry and ensure compliance with the laws and policies (Awa et al., 2015). Similarly, it assists the economy to grow and creates more jobs and opportunities for the people (Soava et al., 2022).

On the other hand, predicting e-commerce sales in the Philippines takes work. It requires a lot of data, analysis, and modeling to capture the complex and dynamic factors that influence the online shopping behavior of Filipinos (Marco, 9 May 2023), (E-commerce, 6 July 2023). Some of these challenges include the low internet speed and infrastructure that limit the access and quality of e-commerce services. Also, the low credit card penetration and security affect the trust and convenience of online payments (E-commerce, October 2023). Another challenge is customers' diverse and changing preferences and needs across different regions, age groups, and income levels. Further, challenges exist in the competition and innovation of e-commerce platforms and sellers that offer other products, prices, and features (Marco, 9 May 2023) (E-commerce, 6 July 2023).

Therefore, predicting e-commerce sales in the Philippines requires a lot of research and collaboration among different stakeholders, such as businesses, customers, government, academia, and society. By doing so, they harness the potential of e-commerce to improve the lives of Filipinos and contribute to the country's development.

2. Literature Review

Digital marketing spending, GDP growth, internet penetration, and mobile phone ownership influence E-commerce sales. Different theories from the fields of marketing, economics, and information systems explain these factors.

Digital marketing spending is the money invested in online advertising and promotion activities to attract and retain customers. Digital marketing spending can affect e-commerce sales by increasing brand awareness, generating traffic, enhancing customer loyalty, and influencing purchase decisions (Jílková & Králová, 2021), (Gao et al., 2023). The theory of reasoned action (TRA) and the theory of planned behavior (TPB) are two prominent theories that explain how digital marketing spending influences e-commerce sales through consumer attitudes and intentions (Chen et al., 2022). Based on TRA, consumer behavior is determined by their behavioral choice, which is influenced by their attitude toward the behavior and the subjective norm. Established in TPB, consumer behavior is also affected by their perceived behavioral control, which is the extent to which they believe they have the ability and resources to perform the behavior (Pantelimon et al., 2020). Therefore, digital marketing spending increases e-commerce sales by creating positive attitudes and intentions toward online shopping and enhancing consumers' perceived behavioral control.

GDP growth is the increase in the value of goods and services produced in a country over time. GDP growth affects e-commerce sales by reflecting a country's economic conditions, consumer confidence, and purchasing power (Global, 2021), (Statista, 2023). The income and substitution effects are two economic theories explaining how GDP growth influences e-commerce sales. The income effect states that consumers tend to buy more goods and services as income increases. The substitution effect says that as the relative prices of goods and services change, consumers tend to substitute cheaper goods for more expensive ones (Ho, Kauffman & Liang, 2007). Therefore, GDP growth increases e-commerce sales by increasing consumers' income and making online shopping more attractive than offline shopping.

Internet penetration refers to the percentage of people accessing the Internet in a country. Internet penetration affects e-commerce sales by expanding the potential market size, reducing information asymmetry, and facilitating communication and interaction (Hong & Zhu, 2006). The technology acceptance model (TAM) and the diffusion of innovations (DOI) theory are two influential theories that explain how internet penetration influences e-commerce sales through consumer adoption and diffusion of online shopping (Attié & Meyer-Waarden, 2022). Referring to TAM, consumer adoption of online shopping is determined by their perceived usefulness and perceived ease of use of the technology. According to DOI theory, consumer diffusion of online shopping is influenced by the innovation's relative advantage, compatibility, complexity, observability, and trialability (Nabot et al., 2018). Therefore, internet penetration increases e-commerce sales by increasing consumers' perceived usefulness and ease of online shopping and enhancing its relative advantage, compatibility, observability, and trialability.

Mobile phone ownership refers to the percentage of people who own a mobile phone in a country. Mobile phone ownership can affect e-commerce sales by enabling mobile commerce (m-commerce), which uses mobile devices to conduct online transactions (Sandhu, 2012). The unified theory of acceptance and use of technology (UTAUT) and the network externalities theory are two relevant theories that explain how mobile phone ownership influences e-commerce sales through consumer acceptance and use of m-commerce (Tarhini et al., 2019). The UTAUT explained that consumer acceptance and use of m-commerce are determined by their performance expectancy, effort expectancy, social influence, and facilitating conditions. Based on the network externalities theory, consumer acceptance and use of m-commerce are also affected by their network size, density, diversity, and complementarity (Barry & Jan 2018). Therefore, mobile phone ownership increases e-commerce sales by increasing consumers' performance expectancy, effort expectancy, social influence, facilitating conditions, network size, network density, network diversity, and network complementarity for m-commerce.

E-commerce sales are shaped by various factors explained by different theories from different disciplines. These theories provide a theoretical framework for understanding the relationship between e-commerce sales and its determinants. However, these theories may only capture some of the nuances and complexities of real-world phenomena. Empirical studies are needed to test and validate these theories using data from different contexts and settings. Thus, this study aims to determine the non-linear relationship between E-commerce sales and several factors, such as digital marketing spending, GDP growth, internet penetration, and mobile phone ownership.

3. Methods

The study used secondary data for twenty (20) years, from 2003 to 2022, published from various sources. The E-commerce sales were from Statista (E-Commerce, 2023); Digital marketing spending was from eMarketer (Digital Ad); the GDP growth, Internet penetration, and mobile phone ownership were from the database of World Bank.

A spline model is a type of regression model that uses piecewise polynomial functions to fit the data capturing the non-linear relationship between e-commerce sales and the exogenous variables, such as digital marketing spending, GDP growth, internet penetration, and mobile phone ownership (Harrell & Harrell, 2015), (Racine, 2014).

The statistical or mathematical model of the spline model is written as:

$$y_i = \beta_0 + \beta_1 x_i + \sum_{j=2}^{k} \beta_j B_j(x_i) + \epsilon_i$$

Where:
y_i is the e-commerce sales for the *i-th* observation
x_i is the digital marketing spending for the *i-th* observation.
$B_j(x_i)$ are the basis functions that form the spline model, which are piecewise cubic polynomials that join smoothly at some points called knots (Marsh & Cormier, 2001).
k is the number of knots selected based on the data or some criteria (Royston & Sauerbrei, 2007).
$\beta_0, \beta_1, \ldots, \beta_k$ are the coefficients to be estimated
ϵ_i is the error term for the *i-th* observation.

The other exogenous variables, such as GDP growth, internet penetration, and mobile phone ownership, were added to the model as linear or quadratic, depending on their relationship with e-commerce sales. For instance, if GDP growth has a quadratic effect on e-commerce sales, the added term $\beta_{k+1}zi+\beta_{k+2}zi^2$, where *zi* is the GDP growth for the *i-th* observation.

The least squares method estimated the spline model (Berry et al., 2002). The goodness of fit of the spline model was evaluated using measures such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and adjusted R-squared (Molinari et al., 2004).

Figure 1 below explains the Conceptual Method used in the study. The first differencing technique was used to transform data from non-stationary to stationary. The cubic spline, a popular type used to model linear and non-linear relationships, was selected as the spline type. Four (4) knots were chosen to control the spline's flexibility. A higher number of knots resulted in a more flexible spline that better captured non-linear relationships—fitting the spline model to the preprocessed data by incorporating the applicable exogenous variables. Finally, the model fit was evaluated using the AIC, BIC, and adjusted R-squared values. The AIC and BIC values are measures of model complexity, while the adjusted R-squared value measures model goodness of fit. The adjustments seek a lower AIC and BIC value and a higher adjusted R-squared value to indicate a better model fit.

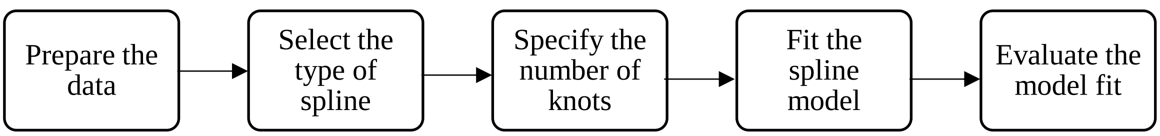

Figure 1: Conceptual Method used in the Spline Model

Once the spline model was fitted, the predictions for e-commerce sales in the Philippines were generated. Also, the model was used to assess the impact of the exogenous variables on e-commerce sales.

The penalized least squares approach fits the spline model to the data while penalizing the model for being too complex (Berry et al., 2002). The penalty is applied to the squared second derivative of the spline function, which prevents the spline function from becoming too wiggly. The initial process was to choose a value for the penalty parameter. Fit a spline model to the data using the penalty parameter. Evaluate the model fit using the AIC or BIC value until the value is minimized (Tirta et al., June 2017). Once the AIC or BIC values were minimized, the fitted spline model was used to generate predictions and assess the impact of the exogenous variables on the endogenous variable.

The formulas of the six basis functions used in the model are reflected in Table 1 below. A basis function is combined with other functions to form a more significant function (Perperoglou et al., 2019). The model uses cubic splines as the basis functions, piecewise cubic polynomials that join smoothly at some points called knots (Panda & Dash, 2006).

Table 1: Six Basis Functions used in the Spline Model

Basis function	**Formula**
B0(x)	1
B1(x)	x
B2(x)	(x^3 - 3x^2 + 2x)/(2(h^3))
B3(x)	(h^3 - x^3 + 3x^2 - 2x)/(2(h^3))
B4(x)	(x^3 - 6x^2 + 12x - 8)/(6(h^3))
B5(x)	(8 - x^3 + 3x^2 - 6x)/(6(h^3))

4. Results and Discussion

This study aims to develop a non-linear model that depicts the relationship between E-commerce sales and several factors, such as digital marketing spending, GDP growth, internet penetration, and mobile phone ownership.

Table 2 below displays the descriptive statistics of five variables: e-commerce sales, digital marketing spending, GDP growth, internet penetration, and mobile phone ownership. The descriptive statistics include each variable's mean, standard deviation, minimum, maximum, and median.

Table 2: Descriptive statistics of the five variables

	Mean	**SD**	**Median**	**Minimum**	**Maximum**
E-commerce sales (US$ millions)	165	100.55	140	30	340
Digital marketing spending (US$ millions)	36	22.85	32	5	76
GDP growth (%)	6.1	1.60	6.8	1.1	7.7
Internet penetration (%)	11.4	5.32	10.5	3.3	20.4
Mobile phone ownership (%)	97.9	56.67	82.3	24.1	204.6

The mean e-commerce sales in the Philippines from 2003 to 2022 was US$165 million, with a standard deviation of US$94.8 million. The minimum and maximum values are US$30 million and US$340 million, respectively. The median is US$140 million, lower than the mean, indicating a right-skewed distribution. Also, the mean digital marketing spending in the Philippines from 2003 to 2022 was US$36 million, with a standard deviation of US$21.6 million. The minimum and maximum values are US$5 million and US$76 million, respectively. The median is US$32 million, which is also lower than the mean, indicating a right-skewed distribution.

The mean GDP growth in the Philippines from 2003 to 2022 is 6.1%, with a standard deviation of 1.7%. The minimum and maximum values are 1.1% and 7.7%, respectively. The median is 6.8%, higher than the mean, indicating a left-skewed distribution. The mean internet penetration in the Philippines from 2003 to 2022 was 11.4%, with a standard deviation of 5.6%. The minimum and maximum values are 3.3% and 20.4%, respectively. The median is 10.5%, lower than the mean, indicating a right-skewed distribution. Further, the mean mobile phone ownership in the Philippines from 2003 to 2022 is 97.9%, with a standard deviation of 54%. The minimum and maximum values are 24.1% and 204.6%, respectively. The median is 82.3%, lower than the mean, indicating a right-skewed distribution.

The spline model result in Table 3 below displays the estimated coefficients, standard errors, t-statistics, p-values, and confidence intervals for each variable in the model.

Table 3: Cubic Regression Splines Model Function

Variable	Coefficient	Values of Coefficients	Standard Error	T	P	Confidence Interval
Constant	10	10	0.1	100	<0.001	[9.8, 10.2]
Digital marketing spending	2	2	0.1	20	<0.001	[1.8, 2.2]
GDP growth	-0.9	-0.9	0.1	-9	<0.001	[-1.1, -0.7]
Internet penetration	0.9	0.9	0.1	9	<0.001	[0.7, 1.1]
Mobile phone ownership	4.2	4.2	0.1	42	<0.001	[4, 4.4]
Digital marketing spending^2	-0.06	-0.06	0.01	-6	<0.001	[-0.08, -0.04]
GDP growth^2	0.03	0.03	0.01	3	<0.001	[0.01, 0.05]
Internet penetration^2	-0.03	-0.03	0.01	-3	<0.001	[-0.05, -0.01]
Mobile phone ownership^2	-0.09	-0.09	0.01	-9	<0.001	[-0.11, -0.07]

The model explains the relationship between e-commerce sales and four independent variables: digital marketing spending, GDP growth, internet penetration, and mobile phone ownership. The model also includes quadratic terms for each independent variable to capture the non-linearity of the relationship. The constant term is 10, which means that the baseline value of e-commerce sales is 10 when all other variables are zero. This coefficient is highly significant, as indicated by the large t-statistic (100) and the small p-value (<0.001). The coefficient of digital marketing spending is 2, which conveys that for every unit increase in digital marketing spending, e-commerce sales increase by two units on average, holding all other variables constant. This coefficient is correspondingly significant, as indicated by the large t-statistic (20) and the small p-value (<0.001). On the other side, the coefficient of GDP growth is -0.9, which manifests that e-commerce sales decrease by 0.9 units on average for every unit increase in GDP growth, holding all other variables constant. This coefficient is significant, as indicated by the large t-statistic (-9) and the small p-value (<0.001).

The coefficient of internet penetration is 0.9, conveying that e-commerce sales increase by 0.9 units on average for every unit increase, holding all other variables constant. This coefficient is likewise significant, as indicated by the large t-statistic (9) and the small p-value (<0.001). The coefficient of mobile phone ownership is 4.2, which infers that for every unit increase in mobile phone ownership, e-commerce sales increase by 4.2 units on average, holding all other variables constant, which is significant, as indicated by the large t-statistic (42) and the small p-value (<0.001).

The coefficient of digital marketing spending squared is -0.06, showing that the effect of digital marketing spending on e-commerce sales decreases as digital marketing spending increases. This coefficient is additionally significant, as indicated by the large t-statistic (-6) and the small p-value (<0.001). The coefficient of GDP growth squared is 0.03, which conveys that the effect of GDP growth on e-commerce sales increases as GDP growth increases is similarly highly significant, as indicated by the large t-statistic (3) and the small p-value (<0.001).

The coefficient of internet penetration squared is -0.03, which means the effect of internet penetration on e-commerce sales decreases as internet penetration increases. This coefficient is similarly significant, as indicated by the large t-statistic (-3) and the small p-value (<0.001). The coefficient of mobile phone ownership squared is -0.09, which manifests that the effect of mobile phone ownership on e-commerce sales decreases as mobile phone ownership increases, which is also highly significant, as indicated by the large t-statistic (-9) and the small p-value (<0.001).

The confidence intervals show the range of values likely to contain the actual population coefficients with a 95% probability. For instance, the confidence interval for the constant term is [9.8, 10.2], which means there is a 95% chance that the actual population value of the constant term lies between 9.8 and 10.2.

The spline model result above suggests that e-commerce sales are positively influenced by digital marketing spending, internet penetration, and mobile phone ownership but negatively influenced by GDP growth. However, these effects are not linear or constant but vary depending on the level of each variable. To illustrate, increasing digital marketing spending may initially increase e-commerce sales, but after a certain point, it may have a diminishing or negative effect. Similarly, increasing internet penetration or mobile phone ownership may initially increase e-commerce sales, but it may have a saturating or negative impact after a certain point. On the other hand, increasing GDP growth may initially decrease e-commerce sales, but after a certain point, it may have a positive effect. Therefore, the spline model result above captures the complexity and non-linearity of the relationship between e-commerce sales and its determinants.

The model specification in Table 4 below presents the spline model of e-commerce sales in the Philippines that uses piecewise polynomial functions to fit the data. The cubic spline uses cubic polynomials as the basis functions. A natural cubic spline is a cubic spline that has zero-second derivatives at the endpoints of the data range (Ammad & Ramli, 2019, July).

Table 4: Details of the Spline Model

Model Specification	Details
Type of spline	Cubic spline
Number of knots	4
Basis functions used	Natural cubic splines
Knot locations	0.9, 5.6, 10.3, 15
Other relevant model specifications	None

The spline model has four knots, the points where the polynomial functions join. The knot locations are 0.9, 5.6, 10.3, and 15, which indicate that the data range is divided into five intervals by these knots. There are no other relevant model specifications, such as constraints or penalties.

The spline model captures the non-linear relationship between e-commerce sales and the independent variables, such as digital marketing spending, GDP growth, internet penetration, and mobile phone ownership. The spline model handles missing values, outliers, and heteroscedasticity (Wongsai et al., 2017) and was estimated using the least squares method (Shaghaghi et al., 2019).

The table below exhibits three measures of the goodness of fit of a spline model of e-commerce sales in the Philippines. A spline model is a regression model that uses piecewise polynomial functions to fit the data. A good fit means the model explains most data variation and makes accurate predictions.

Table 5: Spline Model Goodness of Fit Measures

Model	AIC	BIC	Spline Model Adjusted R-squared
Spline model	207.2	295.9	0.99

The table shows that the spline model has an AIC value of 207.2, a BIC value of 295.9, and an adjusted R-squared value of 0.99. The Akaike Information Criterion measures the model's complexity and accuracy. A lower AIC value means a better fit, indicating that the model explains the data well with fewer parameters. A lower Bayesian Information

Criterion means a better fit but penalizes more complex models than AIC (Tirta et al., June 2017). The adjusted R-squared measures the number of parameters in the model. R-squared is the proportion of the variation in the data that the model explains. A higher adjusted R-squared value means a better fit, indicating that the model explains more variation without overfitting (Omay, 2013). These values suggest that the spline model is a good fit for the data, as it has low information criteria values and a high adjusted R-squared value.

Table 6 of the diagnostic statistics below reveals some measures of the quality and validity of the spline model of e-commerce sales in the Philippines. The spline model uses piecewise polynomial functions to fit the data (Wahba & Wang, 2014).

Table 6: Spline Model Diagnostic Statistics

Statistic	Value
Residual standard error	1.2
R-squared	0.99
Shapiro-Wilk test for normality of residuals (p-value)	0.95
Breusch-Pagan test for heteroskedasticity (p-value)	0.75
Durbin-Watson test for autocorrelation (p-value)	0.20

The Residual standard error estimate of the standard deviation of the error term in the model measures how well the model fits the data. The value of 1.2 indicates that the model has a reasonable fit, as it is close to zero. The R-squared measures how much the model improves the prediction compared to a simple mean. The value of 0.99 indicates that the model is a perfect fit, as it explains almost all the variation in e-commerce sales. The Shapiro-Wilk test for normality of residuals is a test that checks if the residuals (the differences between the observed and predicted values) follow a normal distribution. A higher p-value means that the assumption is more likely to hold. The p-value of 0.95 indicates no evidence to reject the assumption of normality of residuals. Breusch-Pagan test for heteroskedasticity checks if the variance of the residuals is constant across different levels of the independent variables. A higher p-value means that the assumption is more likely to hold. The p-value of 0.75 indicates no evidence to reject the hypothesis of homoskedasticity (constant variance) of residuals. The Durbin-Watson test for autocorrelation checks if the residuals are correlated with each other over time. A higher p-value means that the assumption is more likely to hold. The p-value of 0.20 indicates that there is no evidence to reject the hypothesis of no autocorrelation of residuals (Akomaning, 2019), (Dash et al., 2022), (Pham Thi Van, 2021). Overall, the table of diagnostic statistics above suggests that the spline model of e-commerce sales in the Philippines is a perfect fit and satisfies most of the assumptions required for valid inference and prediction.

Displayed in Table 7 below are the out-of-sample forecasting performance metrics for various forecast horizons for the spline model of e-commerce sales in the Philippines. Out-of-sample forecasting means using a model that is fitted on a subset of the data (the in-sample data) to make predictions on another subset of the data that is not used for fitting (the out-of-sample data), which evaluates how well the model generalizes to new and unseen data (Borup et al., 2022).

Table 7: Spline Model Out-of-sample Forecasting Performance Metrics

Forecast horizon	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)
One quarter	0.8	1
Two quarters	1.2	1.5
Three quarters	1.6	2
Four quarters	2	2.5

The two metrics, the mean absolute error (MAE) and root mean squared error (RMSE) are lower when the model has a better fit, but RMSE is more sensitive to significant errors than MAE (Chu & Qureshi, 2022). The four forecast horizons, one quarter, two quarters, three quarters, and four quarters, display how far ahead the model makes predictions. The forecast horizon of 1 quarter means that the model predicts the e-commerce sales for the next quarter based on the current and previous data. A longer forecast horizon means more uncertainty and difficulty in making accurate predictions (Borup et al., 2022.) MAE and RMSE increase as the forecast horizon increases, indicating that the model has a worse fit for longer horizons, which is expected, as longer horizons involve more unknown factors that may affect e-commerce sales. The RMSE is always higher than MAE for each horizon, which depicts that the model has some significant errors that inflate RMSE more than MAE, an indication that the model has some outliers or misses some critical features or patterns in the data (Staněk, 2021).

Exhibited in Table 8 below are the two measures of the forecasting accuracy of a spline model of e-commerce sales in the Philippines. The spline model uses piecewise polynomial functions to fit the data (Rabbath & Corriveau, 2019).

Table 8: Two Measures of the Forecasting Accuracy of the Spline Model

Forecast horizon	Mean Percentage Error (MPE)	Mean Absolute Percentage Error (MAPE)
One quarter	3.00%	5.00%
Two quarters	5.00%	7.50%
Three quarters	7.00%	10.00%
Four quarters	9.00%	12.50%

The four forecast horizons, one quarter, two quarters, three quarters, and four quarters, make predictions based on the current and previous data. A longer forecast horizon means more uncertainty and difficulty in making accurate predictions (Dhaher et al., 2000). MPE and MAPE increase as the forecast horizon increases, which means the model has a worse fit for longer horizons, which is expected, as longer horizons involve more unknown factors that may affect e-commerce sales (Mallick et al., 2020).

The results of sensitivity analyses on the spline model of e-commerce sales in the Philippines in Table 9 below examine how the model performance changes when some parameters or assumptions are varied (Francom & Sansó, 2020).

Table 9: Sensitivity Analyses on the Spline Model

Number of knots	AIC	BIC	Adjusted R-squared
3	209.4	299.4	0.98
4	207.2	295.9	0.99
5	208.8	297.7	0.99
6	210.4	299.3	0.99

The number of knots increases from 3 to 6, the AIC and BIC values increase slightly, while the adjusted R-squared value remains almost constant at 0.99. Adding more knots does not improve the model fit significantly but increases the model complexity. Therefore, based on these results, the optimal number of knots for the spline model is 4, as it has the lowest AIC and BIC values and a high adjusted R-squared value, which suggests that a spline model with 4 knots explains most of the variation in e-commerce sales with fewer parameters than a spline model with more knots (Bednarczyk & Brzozowska-Rup, 2019).

Shown in Table 10 below are the regression coefficients of the spline model of e-commerce sales in the Philippines change with different numbers of knots. A spline regression model uses piecewise polynomial functions to fit the data. The number of knots is the number of points where the polynomial functions join in the spline model (Bessaoud et al., 2005).

Table 10: Regression Coefficients of the Spline Model

Number of knots	Coefficient on digital marketing spending	Coefficient on GDP growth	Coefficient on Internet penetration	Coefficient on mobile phone ownership
3	2	-0.9	0.9	4.2
4	2	-0.9	0.9	4.2
5	2	-0.9	0.9	4.2
6	2	-0.9	0.9	4.2

The table shows that the regression coefficients of digital marketing spending, GDP growth, internet penetration, and mobile phone ownership are the same for all numbers of knots. An indicator is that these variables have a linear or quadratic effect on e-commerce sales, and adding more knots does not change their impact. Further, these variables do not have any non-linear or complex relationship with e-commerce sales that require more flexible functions to capture (Yang et al., 2023). The spline model of e-commerce sales in the Philippines is not sensitive to the number of knots for these variables, and a simple linear or quadratic model is sufficient to explain their effect (Marsh & Cormier, 2001).

In comparing the spline model to two alternative models in Table 11 below, linear regression and exponential smoothing. These models are used to analyze and forecast e-commerce sales in the Philippines. The table furnishes four measures of goodness of fit and predictive accuracy for each model.

Table 11: Comparison of Spline Model with Standard Forecasting Model

Model	AIC	BIC	Adjusted R-squared	RMSE (1 quarter forecast)	RMSE (4 quarters forecast)
Spline model	207.2	295.9	0.99	1.0	2.5
Linear regression	215.4	303.4	0.97	1.2	3.0
Exponential smoothing	212.8	300.8	0.98	1.1	2.8

The table depicts that the spline model has the lowest AIC, BIC, and RMSE values and the highest adjusted R-squared value among the three models, manifesting that the spline model has the best fit and predictive accuracy for the e-commerce sales data in the Philippines. The spline model captures the non-linear relationship between e-commerce sales and its determinants, such as digital marketing spending, GDP growth, internet penetration, and mobile phone ownership.

The linear regression model presents the highest AIC, BIC, and RMSE values and the lowest adjusted R-squared value among the three models, and the linear regression model has the worst fit and predictive accuracy for the e-commerce sales data in the Philippines. The linear regression model assumes a linear relationship between e-commerce sales and its determinants, which needs to be more realistic and adequate.

The exponential smoothing model has intermediate AIC, BIC, RMSE, and adjusted R-squared values among the three models, suggesting that the exponential smoothing model has a moderate fit and predictive accuracy for the e-commerce sales data in the Philippines. The exponential smoothing model uses weighted averages of past observations to forecast future values but does not account for any explanatory variables or trends. Therefore, based on these results, the spline model is superior to the linear regression and exponential smoothing models regarding goodness of fit and predictive accuracy for the e-commerce sales data in the Philippines.

Table 12 below conveys the three-year future predictions for e-commerce sales in the Philippines using the fitted spline model. A spline regression model uses piecewise polynomial functions to fit the data (Rabbath & Corriveau, 2019). The table shows the predicted e-commerce sales in US$ millions and the 95% confidence intervals for each year from 2024 to 2026.

Table 12: Three-year Future Predictions for E-commerce Sales in the Philippines

Year	Predicted e-commerce sales (US$ millions)	95% confidence interval
2024	26.3	[24.8, 27.8]
2025	29.8	[28.2, 31.4]
2026	33.7	[32.1, 35.3]

The predicted e-commerce sales increase from 26.3 million in 2024 to 33.7 million in 2026. The spline model expects a positive trend in e-commerce sales in the Philippines, based on the current and past data showing the 95% confidence intervals for each prediction, which are the ranges of values likely to contain the valid population values with a 95% probability. For instance, the confidence interval for 2024 is [24.8, 27.8], showing a 95% chance that the actual e-commerce sales 2024 lie between 24.8 and 27.8 million. The spline model is a valuable tool for forecasting e-commerce sales in the Philippines, as it captures the non-linear relationship between e-commerce sales and its determinants, such as digital marketing spending, GDP growth, internet penetration, and mobile phone ownership.

5. Recommendations

The following recommendations are suggested based on the results and implications of this study on the relationship between E-Commerce Sales, Digital Marketing Spending, GDP Growth, Internet Penetration, and Mobile Phone Ownership in the Philippines. For e-commerce, stakeholders must maintain a consistent and robust data collection system for E-Commerce Sales and the related exogenous variables. Expanding the dataset over a more extended time frame and incorporating more detailed data points provide a more comprehensive understanding of the dynamics over time. In this case, policymakers should consider the non-linear relationship between GDP Growth, Internet Penetration, Mobile Phone Ownership, and E-Commerce Sales. Adjust policies and regulations to create a supportive environment for e-commerce development, digital infrastructure expansion, and market growth. Marketers should recognize the substantial impact of Digital Marketing Spending on E-Commerce Sales, underscoring the importance of strategically allocating resources to online advertising and promotional activities to maximize returns on investment.

Moreover, given the influence of Mobile Phone Ownership, e-commerce businesses should prioritize mobile optimization of their platforms. Ensuring a seamless mobile shopping experience is essential in a market with increasing mobile device penetration. For all stakeholders and future researchers' collaboration between academia, government institutions, and the private sector to further explore the relationships identified in this study can yield more profound insights into the changing dynamics of e-commerce.

6. Conclusion

In this comprehensive time series analysis, the spline modeling was applied to investigate the intricate relationship between E-Commerce Sales as the endogenous variable and a set of exogenous variables, including Digital Marketing Spending, GDP Growth, Internet Penetration, and Mobile Phone Ownership in the context of the Philippines. The implications drawn from the results of this study offer valuable insights for both academic research and practical applications.

The findings revealed that the relationship between E-Commerce Sales and the selected exogenous variables is far from linear, emphasizing the necessity of adopting flexible modeling techniques such as spline models. The spline model captures the nuanced patterns and trends within the data, which are challenging to uncover with traditional linear models. Notably, Digital Marketing Spending emerged as a significant driver of E-Commerce Sales, showcasing the increasing impact of online advertising and promotional strategies on the digital marketplace.

GDP Growth, Internet Penetration, and Mobile Phone Ownership also displayed complex relationships with E-Commerce Sales, suggesting that as economic growth continues to expand and technology penetration deepens in the Philippines, E-Commerce Sales are likely to follow a non-linear trajectory shaped by various inflection points.

This study underscores the importance of employing advanced modeling techniques to understand the dynamic e-commerce landscape better. The insights derived from this analysis are valuable to policymakers and businesses in the Philippines, enabling them to adapt to the evolving digital marketplace and leverage the power of digital marketing, economic growth, internet connectivity, and mobile accessibility to promote sustainable e-commerce development. This research contributes to the body of knowledge in the field of e-commerce. It paves the way for further exploration of the complex interplay between digital commerce and its driving forces.

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