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# Modified Bass Diffusion Model to Study Adoption of Covid – 19 Vaccines in The Philippines: Input for Inoculation Rollout

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## ABSTRACT

This study aimed to identify a model that better predicts future trends in adopting Covid-19 vaccines in the Philippines. A non-experimental quantitative research design using modeling techniques was applied. To that effect, this study implemented two diffusion models: the Bass model and the modified Bass diffusion model incorporating vaccine supply, and Google searches, analyzed their predictive abilities, and determined the model that fits better with the observed data. Metric criteria for data analysis include Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), R2, and the Akaike Information Criterion (AIC). The results revealed that when plotted over time, the cumulative number of adopters follows, but not substantially, an S-shaped curve. The modified Bass diffusion model incorporating vaccine supply and Google searches described the adoption of Covid–19 vaccines more accurately and improved the forecast accuracy of the benchmark model by approximately 10%. Moreover, the Philippines expected to reach herd immunity with 90% as a threshold on September 4 – 17, 2022, when the percent of change of the cumulative vaccine supply and Google searches is 0.5%. The policy recommendation is proposed based on the findings of the study. Furthermore, future researchers may utilize the proposed model using the data in another set to confirm its predictive ability.

## INTRODUCTION

Since its first reported case in Wuhan City, the capital province in China, the battle against the novel coronavirus (Covid-19) has not concluded. Among various interventions, from wearing masks to partial and complete lockdowns, mass vaccination seems to be the only way to end the Covid-19 pandemic and enable people to resume their normal lives (Kim & Rao, 2021). In the Philippines, vaccination officially began on March 1, 2021, shortly after the arrival of the first batch of vaccines from Sinovac (Department of Health, 2021). In one year, it only inoculated 57% (62 million Filipinos) of the entire population (Our World In Data, 2022a). This rollout is way below the Government's target of fully vaccinating 77 million Filipinos by the first quarter of 2022 (Clapano, 2021). Globally, the Philippines ranks 69th in vaccination rollout and lags behind peers in Southeast Asia, trailing 82% of Vietnam, 84.4% of Taiwan, and 84.7% of Malaysia (Our World In Data, 2022b). The government has pronounced to raise the herd immunity threshold to 90% of the country's total population (Valente, 2021). However, with this slow pace and a low rate of vaccination rollout, essential questions emerge concerning how and when the government will achieve this target. This is necessary before fully opening activities for economic recovery and returning to normalcy.

By forecasting the total number of fully vaccinated people in the country at any given time, it can be approximated how much of the population needs to be vaccinated and how close the threshold level for herd immunity has been achieved. A recent study conducted by Cihan (2021) applied ARIMA Modeling to forecast the fully vaccinated people against Covid – 19 and examine the future vaccination rate for herd immunity in the US, Asia, Europe, Africa, South America, and the World. The results show that 41.8 percent of Americans, 2.3 percent of Asians, 17 percent of Europeans, 0.6 percent of Africans, 8.8 percent of South Americans, and 5.6 percent of the global population will be fully vaccinated against Covid - 19. This means that countries are still far from reaching the herd immunity threshold required to stop or slow down the Covid – 19 epidemics. The result is significant for public health officials to design intervention programs to speed up vaccination rates. On the other hand, Kim and Rao (2021) used vaccination data from the state of Michigan and applied the Bass diffusion model to predict how vaccines would spread and whether a reward system could lead to herd immunity. Indeed, the incentive program improved immunization rates by 44.19 percent. The implications are significant for policymakers who want to introduce incentive programs to increase vaccination rates in places where such rates are still insufficient to achieve herd immunity.

The most successful adoption of a public health program results from understanding the target population and the factors influencing their rate of adoption. These factors include limited supply and inefficient distribution (Su *et al.*, 2021& Hyder *et al.*, 2021). Other studies found that low Covid – 19 vaccines' uptake was attributed to hesitancy (Marzo *et al.*, 2022; Amit *et al.*, 2022; Cerda & Garcia, 2021), demographics (Harapan *et al.*, 2020; Mo *et al.*, 2021; Cheong *et al.*, 2021), and skepticism, refusal, and anti-vaccine movements (Amit *et al.*, 2022; Al-Jayyousi *et al.*, 2021). According to a study conducted among nurses, frequent exposure to social media and interpersonal interaction are favorably connected with vaccination

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intentions (Xin *et al*., 2021).

The preceding studies about investigating the factors and predicting the Covid-19 vaccines' uptake using different models significantly contribute to the body of knowledge. Nevertheless, there is a gap in the literature on building a model that would predict vaccination saturation levels to ensure herd immunity in the Philippines, as the setting of the study. Additionally, this paper will attempt to accurately forecast the number of fully vaccinated Filipinos by incorporating the cumulative vaccine supply, and Google searches in the model. On the other hand, this study is not without limitations. First, the Bass diffusion model and its modified form are the only models used in forecasting. Several modelers and researchers use other methods. Second, vaccine supply and Google searches are the only exogenous variables considered in this study. Other variables may affect the adoption of Covid – 19 vaccines among Filipinos. Lastly, the data used in the study are the available data found online. There may be adoptions that do not find their way to the portal. It is not clear if the unavailable data would change the forecasting results.

This study sought to identify a better forecasting model for adopting Covid-19 vaccines in the Philippines. Specifically, this paper aimed to address the following objectives: (1) To present the trend of cases (fully vaccinated) in the adoption of Covid – 19 vaccines from April 2021 to January 2022; (2) To develop a modified Bass diffusion model by including vaccine supply and Google searches; (3) To compare the forecasting performance between the original and the modified Bass diffusion model using Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), R2, and Akaike Information Criterion (AIC); (4) To forecast the next 36 weeks of fully vaccinated Filipinos in the Philippines; and (5) To propose policy recommendations based on the findings of the study.

## METHODOLOGY

### Dataset

This study utilized 44 weeks of information related to adopting Covid–19 vaccines in the Philippines. These comprised cumulative fully vaccinated Filipinos, vaccine supply, and Google searches (see Table 1). The data covered a period of 44 consecutive weeks from March 29 – April 03, 2021(Week 0) to January 23 – 29, 2022 (Week 43); thus, the week as a unit of time t was considered.

The Bass model has four parameters: market capacity, time, innovation coefficient, and imitation coefficient. In principle, the number of parameters should be less than the number of data points. Typically, suppose the number of parameters of a model is fewer than the number of data points. In that case, some optimization processes (like the least-squares' method) can be used to determine the optimal model parameters. An estimate is possible with at least five observations from the time series data. Dataset with 44 observations is large enough to capture the shape fitted to a Bass model.

**Table 1:** Weekly cumulative dataset

| Week (t) | Cumulative Fully Vaccinated | Cumulative Vaccine Supply | Cumulative Google Searches |
|---|---|---|---|
| 0 | | 2525600 | 413 |
| 1 | 131023 | 2525600 | 996 |
| 2 | 191982 | 3025600 | 1433 |
| 3 | 230769 | 3525600 | 1744 |
| 4 | 289536 | 4040600 | 2011 |
| 5 | 451270 | 7571000 | 2407 |
| 6 | 720602 | 7779050 | 2775 |
| 7 | 949939 | 8279050 | 3260 |
| 8 | 1187193 | 8279050 | 3861 |
| 9 | 1519566 | 8329050 | 4214 |
| 10 | 1852884 | 12709050 | 4638 |
| 11 | 2114845 | 14209050 | 5224 |
| 12 | 2485616 | 16209050 | 6012 |
| 13 | 2836518 | 17458650 | 6817 |
| 14 | 3464836 | 20728650 | 7358 |
| 15 | 4649963 | 27829450 | 8031 |
| 16 | 5984113 | 30892220 | 8714 |
| 17 | 8781702 | 33767790 | 9667 |
| 18 | 11253696 | 38182830 | 10578 |
| 19 | 12460436 | 42013180 | 11717 |
| 20 | 13105176 | 48429920 | 12592 |
| 21 | 13777698 | 48792620 | 13272 |
| 22 | 14921785 | 52699160 | 13823 |
| 23 | 16735874 | 54701160 | 14326 |
| 24 | 18498248 | 59266840 | 14695 |
| 25 | 20205824 | 66556750 | 15035 |
| 26 | 21737742 | 75451250 | 15334 |
| 27 | 22903841 | 85348210 | 15731 |
| 28 | 23965667 | 91300010 | 16018 |
| 29 | 25316132 | 94430610 | 16343 |
| 30 | 26925731 | 102888800 | 16655 |
| 31 | 28819787 | 109454750 | 16997 |
| 32 | 31626938 | 122066590 | 17352 |
| 34 | 35339433 | 139713880 | 18014 |
| 35 | 38025832 | 144597810 | 18402 |
| 36 | 40881033 | 153182720 | 18709 |
| 37 | 43466612 | 176297400 | 18915 |
| 38 | 47128205 | 192968725 | 19154 |
| 39 | 49797363 | 200914075 | 19315 |
| 40 | 52179204 | 201064615 | 19714 |
| 41 | 55093289 | 203768485 | 20001 |
| 42 | 57190564 | 203768485 | 20322 |
| 43 | 58783438 | 203768485 | 20537 |

The datasets comprised the time series data of eligible Filipinos fully vaccinated, accessed in the Department of Health portal through an interactive graph (Department of Health, 2022). Fully vaccinated refers to a person who has received either a single-dose of vaccine or both doses of a two-dose vaccine. The datasets excluded eligible Filipinos fully vaccinated abroad. The data points were reflected daily, and it was copied individually to the Microsoft Excel spreadsheet. It was organized according to the purpose of the study.

On the other hand, the dataset for the vaccine supply came from various web-based news sources. Vaccine supply refers to Covid–19 vaccines received by the Philippine government, regardless of brand. It was carefully reviewed for accuracy, cross-referenced, and verified root sources. Lastly, the data for Google searches came from Google trends' popularity indices of the web, news, and YouTube searches of the different search terms related to Covid–19 vaccines (Google, 2022). The sum of these searched terms represented the datapoint for a particular week of Google search.

**Research Materials and Instrument**

This study implemented two candidate models: Bass and the Modified Bass diffusion models.

Bass Diffusion Model

$$n(t) = \left[p + \frac{q}{m}N(t-1)\right][m - N(t-1)] \quad (1)$$

where

N(t-1) = the previous cumulative adopters at the week (t – 1)

m = the market potential (level of saturation)

p = the innovation coefficient (internal influence)

q = the imitation coefficient (external influence).

Modified Bass Diffusion Model

$$n(t) = \left[\left(p + \frac{q}{m}N(t-1)\right)(m - N(t-1))\right]\left(1 + \beta_1\frac{\Delta Cum_{VS(t)}}{Cum_{VS(t-1)}} + \beta_2\frac{\Delta Cum_{GS(t)}}{Cum_{GS(t-1)}}\right) \quad (2)$$

where

$\Delta Cum_{(VS(t))}$ = the change in the cumulative number of vaccine supply in a week (t)

$Cum_{(VS(t-1))}$ = the cumulative number of vaccine supply in a previous week (t – 1)

$\Delta Cum_{(GS(t))}$ = the change in the cumulative number of Google Searchers in a week (t)

$Cum_{(GS(t-1))}$ = the cumulative number of Google Searches in a previous week (t – 1)

$\beta_1$= coefficient of percent change in the cumulative vaccine supply

$\beta_1$ = coefficient of percent change in the cumulative Google Searches

Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), R2, and Akaike Information Criterion were used as metric criteria to assess the accuracy and goodness-of-fit of the model. Previous authors used MAPE and RMSE to evaluate the accuracy of the model (e.g., Li, Chen & Zhang, 2017; Jha & Saha, 2018; Jomnonkwao, Uttra & Ratanavaraha, 2020; Tao, 2020; Yang, 2020). The Equation (3) and Table 2 display the MAPE formula and its interpretation (Li, Chen & Zhang, 2017). The Solver, a Microsoft Excel add-in tool, was used to estimate the MAPE, while the Jamovi free software was utilized to estimate the RMSE. Several studies have utilized Solver (e.g., Larty, 2020; Parvin & Beruvides, 2021) and Jamovi software (e.g., Arora *et al.*, 2020) in their data analysis.

On the other hand, R2 and Akaike Information Criterion (AIC) were utilized to assess the goodness-of-fit of each model (see Gholizadeh, Esmaeili & Goodrum, 2018; Hsu & Wang, 2008; Jha & Saha, 2018; Jiang, 2017; Larty, 2020; Naseri & Elliot, 2013; Tao, 2020). The R2 and Akaike Information Criterion values were determined utilizing the free Jamovi software. Smaller values for MAPE, RMSE, and AIC, and R2 values close to one suggest a better fit for the model.

where,

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|A_t - F_t|}{A_t} \times 100 \quad (3)$$

N = number of observations

$A_t$=Actual value at time t

$F_t$=Forecast value at time t

**Table 2:** Prediction Accuracy Level[10]

| Mean Absolute Percentage Error (MAPE%) | Prediction Ability |
|---|---|
| <10 | Highly Accurate |
| 10 – 20 | Good |
| 21 - 50 | Reasonable |
| >50 | Inaccurate |

**Design and Procedure**

This study utilized the non-experimental quantitative research design employing descriptive and predictive modeling. Descriptive statistics were used to describe the basic characteristics of the data used in the study providing simple summaries regarding the samples and measures. In predictive modeling, the purpose is to construct a model that predicts new data values from previous observations. This method was based on mathematical models, which rely on mathematical computations. According to Ali (2020), modeling analyzes current and past data and projects what it learns onto a developed model to estimate the most likely outcomes. Hence, this design was appropriate for exploring the existing 44 cumulative datasets of the weekly adoption of Covid – 19 vaccines from April 2021 to January 2022, using graphical representations to help reveal insights and trends.

The following steps were undertaken to achieve the objectives of the present study. First, permission to conduct the study was asked from the Ethics Review Committee of the University of Mindanao. When it was granted, the author started gathering publicly available data related to Covid – 19 vaccines' uptakes in online sources.

The data underwent cleaning and organizing to omit entries capable of distorting the diffusion process. Second, the author developed his own model for forecasting from the benchmark model (Bass diffusion model). These models (the proposed model and the Bass model) were candidate models for fitting the observed dataset. Third, the data were encoded in the Microsoft Excel spreadsheet. The models were created by converting each Equation to its corresponding formula.

The partial model representation is in Figure 2. Fourth is the graphical analysis and interpretation of numerical data. Fifth, it was necessary to validate the model's generalizability; thus, data splitting was undertaken. The models were tested on two sub-samples, and metric measures were compared. The first half served as a training set, while the second half served as a testing set.

Bass Diffusion Model

$$n(t) = \left[p + \frac{q}{m}N(t-1)\right][m - N(t-1)]$$

| Week(t) | Actual | Predicted | Predicted Cumulative | Absolute Percent Error |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 |
| 1 | 131,023 | 95,726 | 95,726 | 27 |
| 2 | 191,982 | 108,485 | 204,211 | 6 |
| 3 | 230,769 | 122,918 | 327,129 | 42 |
| 4 | 289,536 | 139,237 | 466,366 | 61 |
| 5 | 451,270 | 157,678 | 624,044 | 38 |
| 6 | 720,602 | 178,506 | 802,550 | 11 |
| 7 | 949,939 | 202,013 | 1,004,563 | 6 |
| 8 | 1,187,193 | 228,524 | 1,233,087 | 4 |
| 9 | 1,519,566 | 258,396 | 1,491,483 | 2 |
| 10 | 1,852,884 | 292,022 | 1,783,505 | 4 |

| | |
|---|---|
| m | 112,000,000 |
| p | 0.000854699 |
| q | 0.134253301 |
| MAPE | 18.06 |

**Figure 2:** Partial model representation

Lastly, the model with better forecasting ability predicted the next 36 weeks of Covid – 19 vaccine uptakes in the Philippines.

## RESULTS AND DISCUSSION

### Presentation of the Cumulative Weekly Trend of Fully Vaccinated Filipinos

Shown in Figure 3 is the cumulative number of fully vaccinated individuals in the Philippines from April 2021 to January 2022. In 10 weeks of the vaccination rollout, it only inoculated 1.8 million Filipinos or 1.65% of the total population. The highest Covid – 19 vaccine inoculation in a week was recorded in week 38, with 3.6 million Filipinos fully vaccinated. Furthermore, it can be noted that 50% of the total population was fully vaccinated in 42 weeks. This translates to 57 million fully vaccinated Filipinos.

The cumulative adopters of Covid – 19 vaccines up to the point of inflection represent one–half of the total Philippine population. The graph follows, but not substantially, an S-shaped curve which is a characteristic when the cumulative number of adopters is plotted over time (Rogers, 2003). The insignificant increase in the trend at the beginning indicates a very low rate of adoption of Covid – 19 vaccines among Filipinos in the earlier rollout stage. This could be attributed to barriers of adoption such as availability of supply and inefficient distribution (Tagoe *et al*., 2021), inflexibility of the system (Amit *et al*., 2022), and hesitancy (Marzo *et al*., 2022), among others. A significant increase in the trend was observed from week 15 onwards. This can be explained by the positive word–of–mouth effect from the first adopters of Covid – 19 vaccines. These first adopters are called innovators in the diffusion of innovation paradigm. Their positive interaction in the social system influenced other people to adopt the vaccines. This process continues and gradually increases the cumulative adopters, as depicted in the graph before the point of inflection. Moreover, the government's effort to procure more vaccines and its campaign against misinformation about Covid – 19 vaccines are also contributing factors to this improvement

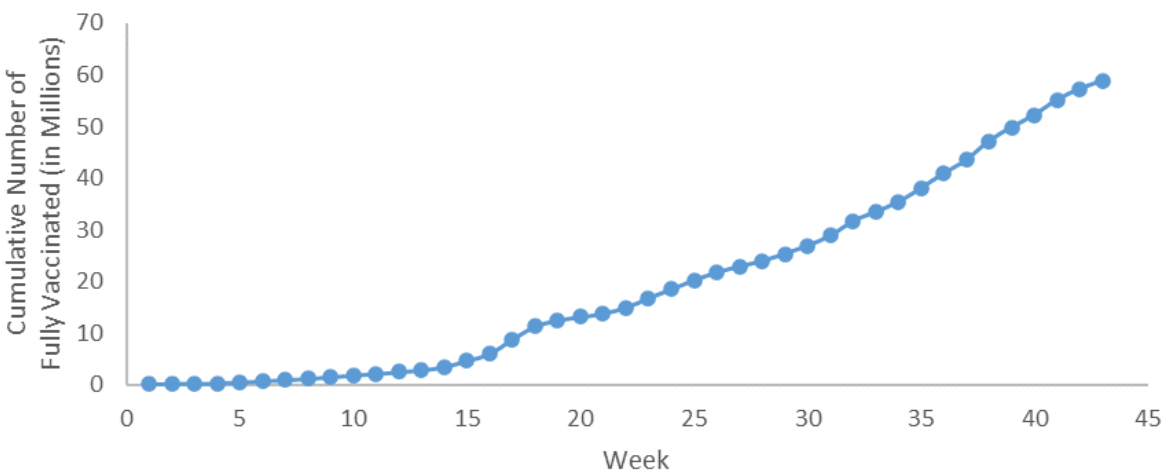


**Figure 3:** Time Series Plot of Cumulative Weekly Number of Fully vaccinated Filipinos from April 04, 2021(Week 1) – January 29, 2022(Week43).

in vaccine uptake among Filipinos (Amit *et al*., 2022)

This finding provides empirical evidence of the Diffusion of Innovation Theory (DOI). It demonstrated how the idea of vaccination spreads over time in the Philippine population. The result of the present study suggests that government and health care providers should improve their Vaccination Deployment Plan. This sluggish vaccination rollout among Filipinos will leave the Philippines vulnerable to its hospitals being overwhelmed with the possibility of another wave of high cases of infections. Moreover, it complicates the government's efforts to reopen the economy and regain growth.

Model Development

This section describes how the researcher modifies the Bass diffusion model by incorporating vaccine supply, and Google searches as exogenous variables and provides its mathematical formulation.

Bass (1969) suggested that the following equation can be used to model the diffusion process:

$$n(t) = \left(p + \frac{q}{m}N(t-1)\right)(m - N(t-1)) \quad (4)$$

where

N(t) = the cumulative number of adopters at time t-1

m = the market potential (saturation level)

p = the coefficient of innovation (internal influence)

q = the coefficient of imitation (external influence).

Bass *et al*. (1994) extended the original Bass model (Equation 4) to the Generalized Bass Model (Equation 5) to include marketing–mix variables advertising and price

$$n(t) = \left[\left(p + \frac{q}{m}N(t-1)\right)(m - N(t-1))\right]x(t) \quad (5)$$

where
$$x(t) = 1 + \beta_1 \frac{\Delta \Pr(t)}{\Pr(t-1)} + \beta_2 \frac{\Delta Ad(t)}{\Pr(t-1)} \quad (6)$$

$$x(t) = 1 + \beta_1 \frac{\Pr(t) - \Pr(t-1)}{\Pr(t-1)} + \beta_2 \frac{Ad(t) - Ad(t-1)}{Ad(t-1)}$$

In Equation (6), $(\Delta\Pr(t))/(\Pr(t\text{-}1))$ and $(\Delta Ad(t))/(Ad(t\text{-}1))$ are percent changes in price and advertising at time t, and the coefficients $\beta_1$ and $\beta_2$ represent how sensitive the diffusion process is to price and advertising.

The author of this paper modifies x(t) from Equation (6) to Equation (7) by replacing marketing–mix variables with exogenous variables, cumulative vaccine supply, and cumulative Google searches. Percent changes of both variables were measured and incorporated into the changes in x(t). For example, Cum(*VS(t)*) - Cum(*VS(t-1)*)/Cum(*VS(t-1)*) means the percent change of the cumulative vaccine supply at time t. The parameters $\beta_1$ and $\beta_2$ were estimated using Nonlinear Least Squares (NLS) method.

$$x(t) = 1 + \beta_1 \frac{\Delta Cum_{VS(t)}}{Cum_{VS(t-1)}} + \beta_2 \frac{\Delta Cum_{GS(t)}}{Cum_{GS(t-1)}}$$

$$x(t) = 1 + \beta_1 \frac{Cum_{VS(t)} - Cum_{VS(t-1)}}{Cum_{VS(t-1)}} + \beta_2 \frac{Cum_{GS(t)} - Cum_{GS(t-1)}}{Cum_{GS(t-1)}} \quad (7)$$

Using Equation (7), Equation (5) becomes

$$n(t) = \left[\left(p + \frac{q}{m}N(t-1)\right)(m - N(t-1))\right]\left(1 + \beta_1 \frac{\Delta Cum_{VS(t)}}{Cum_{VS(t-1)}} + \beta_2 \frac{\Delta Cum_{GS(t)}}{Cum_{GS(t-1)}}\right). \quad (8)$$

where

ΔCum(*VS(t)*) = the change in the cumulative number of vaccine supply in a week (t)

Cum(*VS(t-1)*) = the cumulative number of vaccine supply in a previous week (t – 1)

ΔCum(*GS(t)*) = the change in the cumulative number of Google Searchers in week (t)

Cum(*GS(t-1)*) = the cumulative number of Google Searches in a previous week (t – 1)

$\beta_1$ = coefficient of percent change in cumulative vaccine supply

$\beta_1$ = coefficient of percent change in cumulative Google Searches

Hence, the modified model.

The modified model simply tells us that when x(t) > 1, the adoption process is accelerated and when x(t) = 1, the function returns to the original Bass diffusion model. In no case that x(t) < 1 since the exogenous variables are in cumulative form.

The model developed is the main contribution of this study to the body of knowledge. Although there are several adoption studies in literature, none dealt with modifying an existing model in the context of vaccine adoption in the Philippines as the setting of the study. Moreover, the exogenous variables (supply and Google searches) were added to the model as this contributed significantly to the rate of vaccine adoption. However, future researchers may validate the predictive ability of the proposed model using the data in different setting.

**Forecasting Performance and Predictive Ability Between the Bass and the Modified Bass Model**

This section examines the two candidate model's forecasting performance and predictive ability. The researcher utilizes visual representations through graphs to help reveal insights and trends. Moreover, this study has also grounded on Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), R2, and Akaike Information Criterion as metric criteria for comparison to get a better model which fits well with the observed data.

Shown in Table 3 are the truncated forecast results between Bass and the modified Bass model. To get the predicted value at any given time t, employed in this study are the Equations (4) and (8) for Bass and the Modified model, respectively. It can be observed that the closest Bass model forecasts were in week 12 and week 33 with only +/- 8 adopters, while its farthest forecast was on week 43 with +10, 956, 799 adopters. On the other hand, the modified Bass model's closest forecast was on week 8 with only +11 adopters, while its farthest forecast was on week 18, which underestimated 2,675,227 adopters.

Figures 4 and 5 depict a visual representation of how the predicted values of each model compared with the observed values. It can be observed that the Bass model underestimated the adoption of Covid – 19 vaccines from week 14 (July 04 – 10, 2021) to week 32 (November 7 – 13, 2021) by as large as 5, 895, 661 adopters and overestimated from week 34 (November 21 – 27, 2021) to week 43 (January 23 – 29, 2022) by 10, 956, 799 individuals as the largest difference. On the other hand, it

**Table 3:** Truncated forecast results between Bass and Modified Bass Model

| Week (t) | Observed Data | Bass Predicted | Modified Bass Predicted |
|---|---|---|---|
| 1 | 131,023 | 95,726 | 88,634 |
| 2 | 191,982 | 204,211 | 181,221 |
| 3 | 230,769 | 327,129 | 266,909 |
| 7 | 949,939 | 1,004,563 | 880,066 |
| 8 | 1,187,193 | 1,233,087 | 1,187,204 |
| 9 | 1,519,566 | 1,491,483 | 1,428,976 |
| 10 | 1,852,884 | 1,783,505 | 1,744,330 |
| 11 | 2,114,845 | 2,113,335 | 2,186,380 |
| 12 | 2,485,616 | 2,485,624 | 2,815,063 |
| 13 | 2,836,518 | 2,905,523 | 3,545,301 |
| 14 | 3,464,836 | 3,378,722 | 4,180,088 |
| 17 | 8,781,702 | 5,183,707 | 7,195,573 |
| 18 | 11,253,696 | 5,938,723 | 8,578,469 |
| 19 | 12,460,436 | 6,784,391 | 10,359,508 |
| 33 | 33,462,333 | 33,462,325 | 34,592,594 |
| 34 | 35,339,433 | 36,679,672 | 36,695,669 |
| 42 | 57,190,564 | 66,063,273 | 55,174,325 |
| 43 | 58,783,438 | 69,740,237 | 57,402,852 |

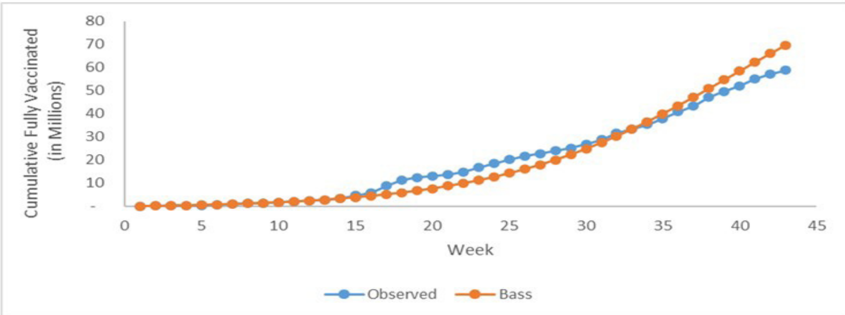


**Figure 4:** Observed and Bass Predicted Time Series Plot of Cumulative Weekly Number of Fully Vaccinated Filipinos from Week 1 – Week 43.

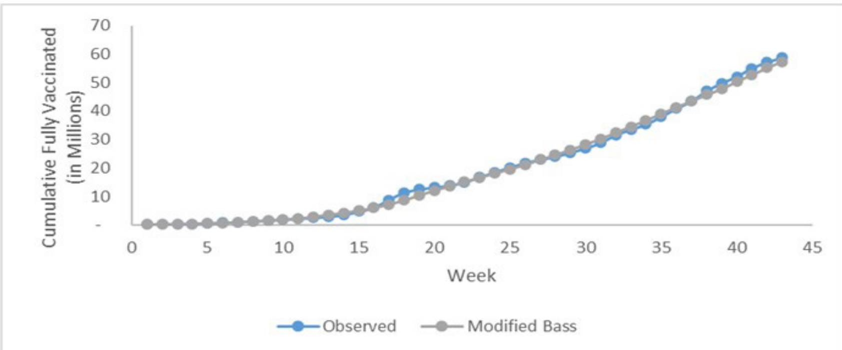


**Figure 5:** Observed and Modified Bass Predicted Time Series Plot of Cumulative Weekly Number of Fully Vaccinated Filipinos from Week 1 – Week 43.

**Table 4:** Model Parameters and Evaluation Criteria

| | Bass Model | Modified Bass Model |
|---|---|---|
| | N = 43 | N = 43 |
| M | 112,000,000 | 112,000,000 |
| p | 0.000855 | 0.000024 |
| q | 0.134253 | 0.063935 |
| $\beta_1$ | na | 0.14 |
| $\beta_2$ | na | 23.08 |
| MAPE | 18.06 | 7.34 |
| RMSE | 3.26e+6 | 998796 |
| $R^2$ | 0.976 | 0.997 |
| AIC | 1418 | 1316 |

can be gleaned that the predicted values generated from the modified Bass model closely match the actual values of fully vaccinated individuals.

Shown in Table 4 are the corresponding parameters of Bass and modified Bass models. It can be gleaned from the table that both the innovation and imitation effects were higher on Bass than on the modified Bass model. On the other hand, the values of Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), R2, and Akaike Information Criterion (AIC) favor the modified Bass model.

The values of p (coefficient of innovation) and q (coefficient of imitation) are both positive for both models, which are plausible. These are within the range of possible values in the review of Bass parameter values conducted by Massiani and Gohs (2015). The corresponding values of R2 and AIC for both models indicate a good fit with the observed data. However, although marginal, compared to the original Bass model (R2 = 0.976 and AIC = 1418), the modified Bass model (R2 = 0.997 and AIC = 1316) suggests a better fit. Furthermore, Mean Absolute Percentage Error (MAPE) is one of the most utilized metrics to assess the model's forecasting accuracy. As reflected in the table, the modified Bass model (MAPE = 7.34%) is highly accurate compared to the original Bass model (MAPE = 18.06%). Compared to the original Bass model's deviation of 18.06 percent, the modified Bass model's deviation from each prediction of the observed data was around 7.34 percent. In other words, the modified model improves the Bass model's accuracy by approximately 10%. The RMSE values indicate the same trend.

The comparison above indicates that modifying the original Bass model improves prediction accuracy. This is aligned with the findings of Kang (2021) when he modified the Bass model to forecast box–office movies and of Jiang (2017) in his study about the diffusion of instant messaging.

One issue in a model–building that needs much attention is its predictive validity. To this end, the author performed data splitting as proposed by Kuhn and Johnson (2013) and followed the procedure by Naseri and Elliott (2013) when they compared Bass, Gompertz, and Logistic models in forecasting online shopping in Australia.

The dataset was split into two sets. The first half will be used as the training set, while the second half will be utilized as the test set. MAPE, RMSE, R2, and AIC were the same metrics used for comparison. The result is presented in Table 5. Overall, the modified Bass model performed better compared to the benchmark model.

The results of the comparison above imply that the forecast accuracy of the original Bass model can be improved by incorporating significant predictors in the model. In the present study, these are vaccine supplies and Google searches. These variables influence the decision among Filipinos to adopt Covid-19 vaccines. This finding of the present study is crucial to policymakers. Access to vaccine supplies to the world market and efficient distribution among its people should be the top priority. Moreover, they should recognize the potential of the internet in disseminating information about Covid-19 vaccination to strengthen public trust.

**Forecasting the next 36 weeks Using the Modified Bass Model**

Based on the result above, the present paper utilized the modified Bass model to forecast Covid – 19 vaccines' uptake among Filipinos from January 30, 2020 (Week 44) to September 17, 2022 (Week 76). Most importantly, the attainment of 90% fully vaccinated Filipinos to ensure herd immunity was forecasted in different scenarios. In building the proposed model, the percent change in cumulative vaccine supply was expressed as

$$r_1 = \frac{Cum_{VS(t)} - Cum_{VS(t-1)}}{Cum_{VS(t-1)}} \quad (9)$$

**Table 5:** Predictive validity of the model

| Model | Week 1 - 22 | | | | Week 23 - 43 | | | |
|---|---|---|---|---|---|---|---|---|
| | MAPE | RMSE | R2 | AIC | MAPE | RMSE | R2 | AIC |
| Bass | 12.78 | 914061 | 0.962 | 672 | inaccurate | 1.24e+6 | 0.903 | 655 |
| Modified Bass | 11.55 | 694721 | 0.978 | 660 | inaccurate | 6930 | 0.989 | 437 |

where

Cum($VS(t)$) = the cumulative vaccine supply at time t

Cum($VS(t-1)$) = the cumulative vaccine supply at time t – 1.

For Google searches, the percent change in cumulative Google searches was expressed as

$$r_2 = \frac{Cum_{GS(t)} - Cum_{GS(t-1)}}{Cum_{GS(t-1)}} \quad (10)$$

where,

Cum($GS(t)$) = the cumulative Google searches at time t

Cum($GS(t-1)$) = the cumulative Google searches at time t – 1.

For this reason, we have evaluated four cases for r. r = 5%, r = 3%, r = 1% and r = 0.5%. As depicted in the figure below, the Philippines will attain herd immunity (with 90% as the threshold) between May 08 – 21, June 05 – 18, July 24 – August 06, and September 04 – 17 of this year when r = 5%, 3%, 1%, and 0.5%, respectively.

Forecasted scenarios indicate that increasing the percent change in cumulative vaccine supplies and Google searches speed up the mass vaccination rollout. This will give the government a perspective on the attainment of herd immunity at the earliest possible time.

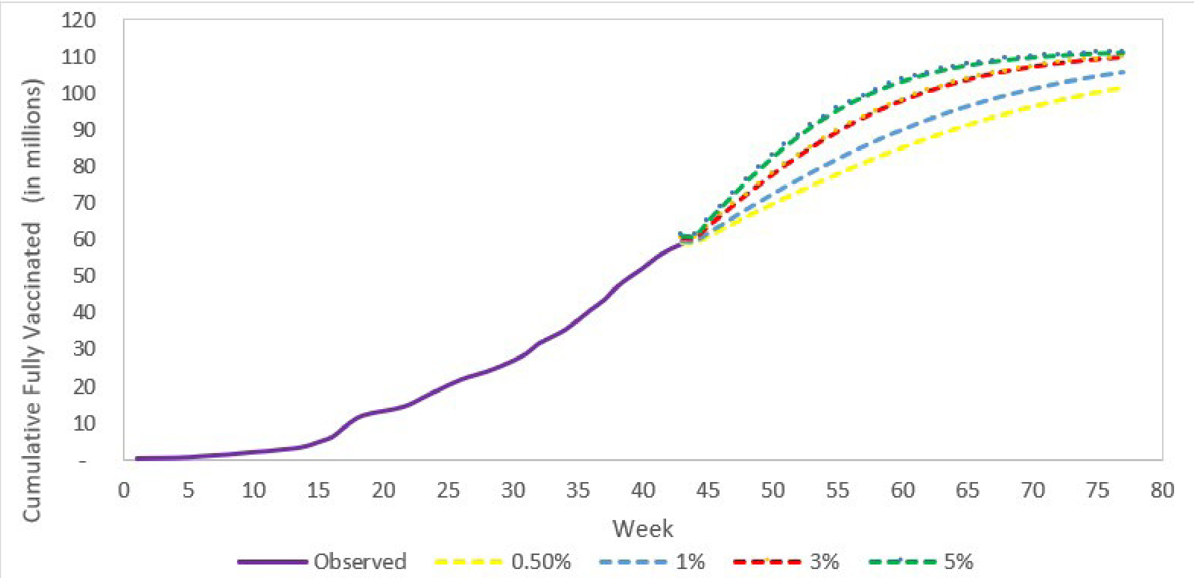


**Figure 6:** Cumulative forecast for Week 44 to Week 76

**Policy Recommendation**

Vaccinating a sufficiently large portion of the Philippine population seems to be the only solution to reaching herd immunity. Although the Philippines shows gradual progress, the vaccination rollout is still low. When this is not addressed, economic recovery and returning to normalcy will be delayed.

This study found out that in one year, it only inoculated 57%(62million) of the country's entire population. Moreover, this study has determined that vaccine supply and Google searches significantly impact the uptake rate of Covid-19 vaccines among Filipinos. These findings suggest that government should secure enough vaccines for its eligible population and consider the potential of the internet for public education about the vaccines. Thus, the following policies are proposed: That the government shall

1. ensure vaccine supply from the global market through bilateral, tripartite, and multilateral agreements,
2. ensure the adequacy of vaccination teams,
3. efficiently distribute the vaccines to priority areas and consider geographic location,
4. implement a mobile vaccination strategy
5. conduct house-to-house vaccination for those senior citizens and bed-ridden who have medical clearance for vaccination,
6. use internet and social media platforms for public information and awareness drive, and
7. initiate a vaccination incentive scheme.

## CONCLUSIONS

This study aims to identify a better forecasting model for adopting Covid-19 vaccines in the Philippines. The results indicate that the modified Bass diffusion model incorporating vaccine supply and Google searches is more accurate than the benchmark model by approximately 10%. This implies that the accuracy of the original model can be improved by introducing significant factors in the model. As such, access to vaccine supply from the world market and considering the potential of the internet and social media platforms for vaccination promotion should be the top priority of the present government to inoculate a sufficiently large size of the country's population. Forecast scenarios from week 44 – week 76 suggest that increasing the percent change of the variables speeds up herd immunity attainment. This will inform the government and the public about attaining its common goal.

The future goal of this study is to forecast the adoption of Covid-19 vaccines in the Philippines using other time series models such as the ARIMA, Gompertz, Logistic, and deep learning. Thus, the performance of the modified Bass model can be compared with the other models. Likewise, future researchers may utilize the proposed model using data in another setting to confirm the model's predictive ability.

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