

A Study on Modeling and Forecasting of Mobile Phone Sales Trends

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이동통신 단말기 판매 추이에 대한 모형 및 수요예측에 관한 연구

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Abstract Among high-tech products, the mobile phone has experienced a rapid rate of innovation and a shortening of its product life cycle. The shortened product life cycle poses major challenges to those involved in the creation of forecasting methods fundamental to strategic management and planning systems. This study examined whether the best model applies to the entire diffusion life span of a mobile phone. Mobile phone sales data from a specific mobile service provider in Korea from March of 2013 to August of 2014 were analyzed to compare the performance of two S-shaped diffusion models and two non-linear regression models, the Gompertz, logistic, Michaelis-Menten, and logarithmic models. The experimental results indicated that the logistic model outperforms the other three models over the fitted region of the diffusion. For forecasting, the logistic model outperformed the Gompertz model for the period prior to diffusion saturation, whereas the Gompertz model was superior after saturation approaches. This analysis may help those estimate the potential mobile phone market size and perform inventory and order management of mobile phones.

요약 하이테크 제품 중에서 이동통신 단말기는 빠른 속도로 혁신이 이루어지고 있으며 이에 따라 제품수명주기도 짧아지고 있다. 이렇게 짧아진 제품수명주기를 정확히 예측하기 위해서는 정확한 수요예측방법론의 선택이 중요하며 이는 전략적 경영계획 수립에 가장 기본적인 요소라고 할 수 있다. 본 연구의 목적은 이동통신 단말기의 전체 확산 수명에 적용될 수 있는 최적의 모형을 제시하는 것이다. 우리는 2013년 3월부터 2014년 8월까지 국내 특정 이동통신 서비스 사업자의 이동통신 단말기 판매 데이터를 활용하여 이동통신 단말기의 판매추이 및 수요예측을 위한 최적의 모형을 제시하고자 한다. 본 연구에서는 네 가지 모형의 성능을 비교분석하였는데 두 가지 S자형 확산모형인 Gompertz와 logistic 모형, 두 가지 비선형 회귀모형인 Michaelis-Menten과 logarithmic 모형을 비교한다. 모형 적합도에 따르면 logistic 모형이 모형일치성에 있어서 다른 세 개의 모형보다 성능이 우수한 것으로 발견되었으며 수요예측모델로는 확산이 정체하기 전까지는 logistic 모형이 우수하며 포화단계에 근접할수록 Gompertz 모형이 적합한 것으로 나타났다. 이러한 분석결과는 이동통신 단말기 시장 규모를 추정하거나 이동통신 단말기의 재고 및 주문관리를 하는데 있어서 유용한 자료로 활용될 수 있을 것이다.

Keywords : Forecasting, Mobile phone sales, S-shaped diffusion model, Non-linear regression model

1. Introduction

Over the past decade, high-tech industries such as consumer electronics, telecommunications equipment,

and semiconductors have experienced an unprecedented rate of acceleration of technology innovations and rapid product introduction cycles. Therefore, these companies are more concerned with keeping pace with

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demand and ensuring availability of their products than with accuracy of the data provided by customers [1]. As mentioned by Tina Teng [2], North America has a shorter replacement cycle of less than two year for cell phone. In particular, because the life cycle of mobile phone tends to be short at less than 24 months, mobile phone vendors face major challenges when developing and deploying new mobile phone given the rapid rate of innovation and mobile service providers face major challenges when optimizing their operations without creating excess inventory or overcapacity of their mobile phone stock. Therefore, mobile phone vendors must provide innovative products in order to retain their customer base and to gain new revenue opportunities. Mobile service providers which provide mobile service with mobile phones supplied by mobile phone vendors must acknowledge the life cycle of new mobile phones and forecast their sales volume for the future.

In order to analyze the diffusion pattern of mobile telephony markets, growth models with an S-shaped curve are applicable in a considerable volume of research [3-6]. The S-shaped curve initially rises slowly then accelerates when the service is widely adopted and then levels off after the inflection point and increases gradually as saturation approaches [6]. Regression analysis has also been applied to mobile telephony markets [7-8]. Wu and Sandrasegaran [8] predict that both of the global system for mobile communications (GSM) and universal mobile telecommunication system (UMTS) markets in Asia Pacific will keep experiencing an exponential growth.

In this paper, we attempt to provide an insight concerning estimation and forecasting for mobile phone sales based on a cumulative data from March of 2013 to August of 2014 in Korea. Towards this goal, two S-shaped diffusion models which are the Gompertz and logistic models and two non-linear regression models which are the Michaelis-Menten and logarithmic models, are employed in order to study their ability to capture diffusion process dynamics. The corresponding

results provide which diffusion model is the most appropriate for Korea and whether the most appropriate diffusion model is consistent in forecasting the cumulative sales value of new mobile phones with real sales data in the early stages after each phone's release. The results of this study may contribute to making of sales predictions for the near future, estimating how many units will be sold overall, and the approximate date of the decline of each mobile phone depending on sales data of each mobile phone in the early stages.

Reliable data sources are the most important factor when making such forecasts. Without sufficient and reliable data, it is impossible to obtain accurate results. In this paper, we use data from a specific mobile service provider in Korea. The dataset used for this analysis contains information on mobile phones which were released to the mobile phone service provider from March of 2013 to August of 2014. The total length of each time series is 18 months, and the time unit here is the month. The software tool selected to analyze trend lines is R for the Gompertz, logistic, and Michaelis-Menten models and Excel for the logarithmic model, because they can be easily accessed without any additional cost.

This paper is organized as follows: In Section 2, we give a brief introduction of the relevant parts of several demand forecasting models and existing forecasting models from the literature in related fields. The next section analyzes the diffusion models and study methodology is then described. The experimental results based on the data from actual mobile phone sales are presented in Section 4 to demonstrate the advantages of the proposed models. Finally, we make conclusions the paper in Section 5.

2. Research Reviews

A new product passes through a sequence of stages from introduction to growth, to maturity, and to decline. Sales of a new product begin with a small

number of customers, grow to a peak at some time, and then decline again, perhaps to zero [9]. This sequence is known as the product life cycle and is associated with changes in the marketing situation, and then impacting the marketing strategy and the marketing mix [10]. Most high-technology products are adopted initially only by people with a keen interest in this type of new technology known as early adopters. Early adopters are often technologically sophisticated, well informed, and not averse to any risks potentially associated with the user of a new product [11]. Rogers [12] notes that the approval of early adopters eventually leads to market saturation and that early adopters are leaders in the trend toward market saturation. Thus, because early adopters influence the market cycle and promote market demand, research about early adopters for demand forecasting is very useful.

The Bass diffusion model [13] presents a rationale of how current adopters and potential adopters of a new product interact. In this model, adopters can be classified as innovators or as imitators and the speed and timing of adoption depends on their degree of innovativeness and the degree of imitation among adopters [13]. Mahajan et al. [14] broadly discuss the characteristic features of diffusion models including the Bass diffusion model. Bass diffusion model also has been compared with other diffusion models to mobile telephony markets [5-6]. Diffusion models such as the Gompertz and logistic models are widely used for forecasting market development [15-16]. These models typically use an S-shaped curve to model cumulative sales up to the end of a time period, which may be thought of as cumulative distribution curves for product life cycles. In mobile telephony markets, a considerable volume of research has been carried out on their diffusion at national [3-6] as well as at international level [17-18]. There are also a number of S-shaped curve applications in different fields, such as technology forecasting and population forecasting [16,19-21].

Moving average methods are used to analyze a set of data points by creating a series of averages of different subsets of the full data set. There are three most commonly used moving average formulas: simple, weighted and exponential. The most recent data is assigned the greatest weight, and each value receives a smaller weight as we count backward in the series. Given that the goal is to forecast future event directions, it may be more effective to assign a greater weight to more recent data points in the time series. Among moving average methods, the remarkably good forecasting performance of the exponentially weighted moving average (EWMA) has been addressed by several authors, the EWMA model is widely used in business and industry [22].

Some forecasting methods use the assumption that it is possible to identify the underlying factors that may influence the dependent variable. Regression analysis is used to investigate the relationship between variables by determining the values of parameters for a function that best fits the input data. With the knowledge of existing data, regression analysis can provide excellent forecasts. There have been numerous studies applying regression analysis in various business contexts, including cosmetics [23], electricity [24], and air quality [25]. Regression analysis has also been applied to mobile telephony markets [7-8]. Although regression analysis is a powerful forecasting tool, it does consider only the impact of regressors. For example, the telecommunication industry is expanding and dynamic and is closely associated with other industries. A new innovation in those other industries can have great effects on the telecommunication industry. It also should be noted that some factors cannot be easily expressed in numerical terms, such as social and political factors [8].

The sales trends curve with a sequence of product life cycle is typically modeled by two functions describing the cumulative and noncumulative spread of the product. Using the noncumulative function, we can easily assess changes in values since the previous data

was published. However, cumulative function may give us usefulness for determining the total value over time and understanding how the total level of data has increased [26]. Park and Oh [23] propose that cumulative data can be simpler to analyze than noncumulative data in a time series. However, cumulative data may be heteroscedastic and ordinary least squares estimators (OLSE) from such data are not the best linear unbiased estimators (BLUE), meaning that the Gauss-Markov theorem does not apply [27]. Therefore, corrections for heteroscedasticity which may occur in cumulative data are needed.

Thus, many technological forecasting methods have been reported in literature, and they have been applied widely [28]. Levary and Han [28] discuss that it is important to determine the forecasting method that will be most appropriate to a given situation, as forecasting results are typically influenced by the forecasting method used.

3. Research Methodology

The S-shaped curve of the growth curve model is a mathematical model that has been applied to cumulative data. The generalized S-shaped curves have three main stages. The initial stage of growth is approximately exponential; then, as saturation begins, the growth slows, and at maturity, growth stops. The cumulative functions can generally have the following characteristics: a symmetric S-shaped logistic distribution, a nonsymmetric S-shaped curve [29]. The Gompertz and logistic models among the S-shaped curves are commonly used to investigate mobile telephony diffusion [3-6,17-18]. In this paper, we utilize the Gompertz and logistic models to investigate mobile phone sales diffusion.

Because the S-shaped curves are performed by using a regression model that tests for non-linearity between the dependent variable (to be forecasted) and time [19], we also select regression analysis as the modeling tool for mobile phone sales diffusion. Generally, because

the curve of cumulative data may be non-linear, we use non-linear regression to fit data to a model. A non-linear regression model is a form of regression analysis in which observational data are modeled by a function which is a non-linear combination of the model parameters. Most popular non-linear regression models for representing growth are using the logarithmic and exponential functions. Among two models, we select the logarithmic model and also introduce the Michaelis - Menten model. The reason why we use the logarithmic and Michaelis - Menten models may be best-fit curves used when the rate of change in the data increases or decreases quickly and then levels out. In addition, the logarithmic model can be used as a fix for heteroscedasticity of cumulative data. Therefore, this section reviews the Gompertz, logistic, Michaelis - Menten, and logarithmic models.

The Gompertz model is expressed as

$$\frac{dN}{dt} = rN \ln \frac{K}{N} \tag{1}$$

where N is the total penetration at time t , r is the diffusion rate with actual penetration, and K is the saturation level. The solution for the first-order differential equation is

$$N(t) = Ke^{-e^{-r(t-m)}} \tag{2}$$

The logistic model is expressed as

$$\frac{dN}{dt} = rN \left(1 - \frac{N}{K}\right) \tag{3}$$

The solution of the first-order differential equation is

$$N(t) = \frac{K}{1 + e^{-r(t-m)}} \tag{4}$$

The Michaelis-Menten model is one of the simplest and best known models of enzyme kinetics in biochemistry. The equation in which the

Michaelis-Menten model [30] based on is as follows:

$$V = \frac{V_{\max} [S]}{K_m + [S]} \quad (5)$$

where V_{\max} represents the maximum rate achieved by the system, at maximum saturation of the substrate concentration. V_{\max} values are expressed in units of product formed per time. K_m is expressed in the units of the substrate concentration that lead to the half-maximal velocity.

The logarithmic model is expressed as

$$\frac{dN}{dt} = \frac{K}{t} \quad (6)$$

The solution of the first-order differential equation is

$$N(t) = K \ln t + C \quad (7)$$

The parameters that are most likely correct are those that generate a curve that minimizes the sum of the squares of the vertical distance between actual value and forecast value. The least-squares regression minimizes: the sum of squares (SS) defined by

$$SS = \sum_{t=1}^n (A_t - F_t)^2 \quad (8)$$

where A_t is the actual value, F_t is the forecast value, and n is the number of observations.

For model fitting, root mean square error (RMSE) is applied as the performance criterion.

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (A_t - F_t)^2} \quad (9)$$

In order to judge the performance of a forecast of a variable with a pronounced trend, we use RMSE and mean absolute percentage error (MAPE) as appropriate measures. The MAPE is a forecast accuracy measure.

MAPE is calculated for all sets of data, and the model with the smallest MAPE is considered to be the most appropriate for forecasting. The measures of RMSE and MAPE for forecasting are modified as follow:

$$RMSE = \sqrt{\frac{1}{m} \sum_{t=1}^m (A_{L+t} - F_{L+t})^2} \quad (10)$$

$$MAPE = \frac{1}{m} \sum_{t=1}^m \left| \frac{A_{L+t} - F_{L+t}}{A_{L+t}} \right| \quad (11)$$

where L is the last month of fitted durations, and m is the number of forecasts.

4. Results

4.1 Model fitting

The rapid replacement rate of mobile phones contributes to shortening their product life cycles, leading to the introduction of various mobile phones. Planning a new mobile phone requires a large number of technical and commercial decisions to be made in advance of the launch of the mobile phone. Many of these decisions depend crucially upon knowing the likely numbers of customers and the likely purchase patterns of these customers. In order to model sales of mobile phone, we use monthly data to fit a proper diffusion model. The dataset used for this analysis comprises sales data of 31 mobile phones which were released by the mobile service provider considered here from March of 2013 to August of 2014.

The software tools used to fit the diffusion models are R for the Gompertz, logistic, and Michaelis-Menten models and Excel for the logarithmic model, because R is free and open source software, allowing anyone to use, and Excel is nearly always included as part of the Microsoft Office software package and then no additional expense is required as Brown [31] mentioned.

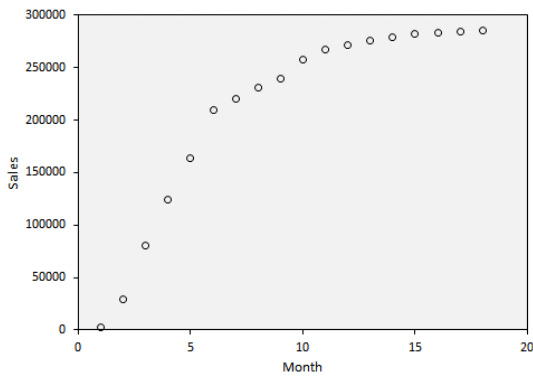


Fig. 1. Cumulative sales data of a specific mobile phone (March of 2013 to August of 2014)

Fig. 1 shows the cumulative sales data of a specific mobile phone for 18 months from March of 2013 to August of 2014. The cumulative sales data of the mobile phone quickly expands early, and then climbs in a lower and steady pattern by the last few months. The trend curve of this cumulative sales data follows the same series of stages of the product life cycle of introduction, growth, maturity and decline. However, the trend line in Fig. 1 shows that the duration from introduction to maturity is very short. For example, the sales growth rate has become slow since the sixth month after the introduction of the new mobile phone. This means that this recently introduced mobile phone has a “short” product life cycle, which characterizes a short lifetime on the market, a steep decline stage and the lack of a maturity stage as discussed Goldman [32].

Table 1 summarizes the performance measures for fitted RMSE of the Gompertz, logistic, Michaelis-Menten and logarithmic models for the cumulative sales data of 31 mobile phones which were released from March of 2013 to August of 2014. From Table 1, it is found that Gompertz or logistic models are more reliable than the Michaelis-Menten or logarithmic because these two models outperform the other two models. It is also noted that the logistic model has the lowest RMSE value in 21 among 31 mobile phones. These results indicate that the logistic model is the fittest model for the cumulative sales data of mobile phones in Korea.

Table 1. Comparison of model fit of four models

| No. | RMSE | | | |
|-------------|-----------|-----------|------------------|-------------|
| | Gompertz | Logistic | Michaelis-Menten | Logarithmic |
| 1 | 7.4.E+03 | 1.2.E+04 | 6.7.E+03* | 7.4.E+03 |
| 2 | 6.3.E+03 | 8.6.E+03 | 6.3.E+03 | 5.6.E+03* |
| 3 | 8.5.E+03* | 9.8.E+03 | 8.5.E+03 | 1.8.E+04 |
| 4 | 6.8.E+02 | 5.8.E+02* | 6.1.E+02 | 8.6.E+02 |
| 5 | 3.3.E+03* | 3.6.E+03 | 3.8.E+03 | 5.6.E+03 |
| 6 | 2.9.E+03* | 3.5.E+03 | 2.9.E+03 | 4.8.E+03 |
| 7 | 5.7.E+03* | 7.8.E+03 | 6.7.E+03 | 6.7.E+03 |
| 8 | 9.4.E+03 | 8.0.E+03* | 1.0.E+04 | 8.4.E+03 |
| 9 | 2.2.E+04 | 9.0.E+03* | 2.2.E+04 | 2.0.E+04 |
| 10 | 7.7.E+03 | 4.8.E+03* | 8.0.E+03 | 9.8.E+03 |
| 11 | 1.3.E+03 | 4.8.E+02* | 2.2.E+03 | 2.9.E+03 |
| 12 | 1.7.E+04* | 2.2.E+04 | 1.8.E+04 | 2.6.E+04 |
| 13 | 7.9.E+03* | 1.3.E+04 | 8.2.E+03 | 1.5.E+04 |
| 14 | 2.0.E+05 | 1.1.E+04 | NC | 6.7.E+04 |
| 15 | 8.4.E+03 | 4.6.E+03* | 8.4.E+03 | 1.1.E+04 |
| 16 | 5.1.E+03 | 5.4.E+03 | 5.5.E+03 | 4.2.E+03* |
| 17 | 4.4.E+04 | 2.1.E+04* | 4.4.E+04 | 6.0.E+04 |
| 18 | 4.7.E+03 | 2.7.E+03* | 6.1.E+03 | 5.4.E+03 |
| 19 | 2.0.E+04 | 1.1.E+04* | 2.2.E+04 | 1.7.E+04 |
| 20 | 3.1.E+04 | 1.8.E+04* | 4.0.E+04 | 3.6.E+04 |
| 21 | 3.9.E+04 | 1.5.E+04* | 4.5.E+04 | 3.9.E+04 |
| 22 | 8.9.E+04 | 1.8.E+04* | 9.9.E+04 | 8.3.E+04 |
| 23 | 4.2.E+03 | 1.5.E+03* | 4.5.E+03 | 4.2.E+03 |
| 24 | 1.3.E+04 | 2.6.E+03* | 1.4.E+04 | 1.4.E+04 |
| 25 | 3.3.E+04 | 1.1.E+04* | 3.6.E+04 | 3.1.E+04 |
| 26 | 2.4.E+04 | 1.2.E+04* | 2.6.E+04 | 2.2.E+04 |
| 27 | 1.4.E+03 | 6.1.E+02* | 1.4.E+03 | 1.4.E+03 |
| 28 | 4.3.E+04 | 1.3.E+04* | 5.2.E+04 | 4.7.E+04 |
| 29 | 5.8.E+03 | 3.5.E+03* | 6.7.E+03 | 6.5.E+03 |
| 30 | 3.9.E+04 | 3.1.E+04* | 4.5.E+04 | 3.6.E+04 |
| 31 | 2.2.E+04 | 9.5.E+03* | 2.7.E+04 | 2.5.E+04 |
| No. of best | 6 | 21 | 1 | 2 |

NC : Not converged.

*Best among the Gompertz, logistic, Michaelis-Menten, and logarithmic models

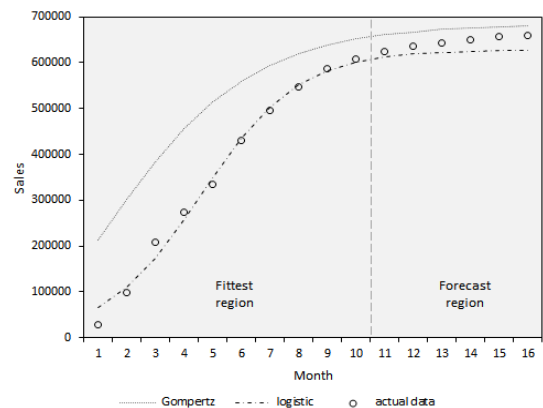


Fig. 2. Forecast curves of Gompertz and logistic models

4.2 Forecasting

From the above observations and analyses, it was found that the cumulative sales data of new mobile phones will experience the Gompertz or logistic growth. According to the Gompertz and logistic models, the cumulative sales value of mobile phones by the end of their life cycles can be forecasted. The dataset used for this forecasting comprises the 10-month sales data of a mobile phone which was released in September of 2014. The estimation results for two models (Gompertz and logistic) are depicted graphically in Fig. 2 and the corresponding numerical results are presented in Table 2. As noted in the previous section, the RMSE and MAPE value are calculated for the performance of the forecast. The logistic model outperforms the Gompertz model in terms of RMSE and MAPE for forecasting period. However, the Gompertz model outperforms the logistic model as saturation approaches (after 14th month).

Table 2. Estimation results and statistical measures of precision

| | | Actual | Gompertz | Logistic |
|--|-----|---------|----------|----------|
| No. of observations | | | 10 | 10 |
| No. of forecasts | | | 6 | 6 |
| Parameter estimation | K | | 6.84E+05 | 6.28E+05 |
| | r | | 3.53E-01 | 5.87E-01 |
| | m | | 1.50E+04 | 3.89E+04 |
| fitted RMSE | | | 1.44E+05 | 1.84E+04 |
| 6-month forecast RMSE | | | 2.80E+04 | 2.40E+04 |
| 6-month forecast MAPE | | | 4.26E-02 | 3.49E-02 |
| total RMSE | | | 1.15E+05 | 2.07E+04 |
| cumulative sales value in the 16 th month | | 660,613 | 679,945 | 627,009 |

Table 2 presents estimation results and statistical measures of precision for the Gompertz and logistic models. According to the performance measures for fitted RMSE, 6-month forecast RMSE and MAPE, and total RMSE for the Gompertz and logistic models, the performance measures in the fitted, the forecasting

region, and total region indicate that the logistic model fit excels, whereas the Gompertz model excels after 14th month. This means that the fittest model is not necessarily that with the best forecasting power, which is consistent with the argument by the previous research [6,33].

Although the Gompertz model fits the initial introduction stage of the mobile phone less adequately, it performs well in forecasting region, especially at the saturation period. However, the fit based on the logistic model is quite acceptable in fitted region but there is an observable divergence in the values at the saturation period. These results are similar with the previous studies [5-6]. The Gompertz curve is a function of non-adopters only, whereas the logistic curve remains a function of both adopters and non-adopters [34]. Thus, if one diffusion process weakly correlates with the number of adopters when the diffusion process slows (e.g. nears saturation), the Gompertz model outperforms the logistic model in forecasting this diffusion process [6]. The major finding of experimental results are as follows. First, logistic model normally outperforms the Gompertz model considering the total product life cycle. Second, logistic model outperforms the Gompertz model for the period prior to diffusion saturation, whereas the Gompertz model is superior after saturation approaches. Therefore, this study demonstrates that the appropriate diffusion model can be stage-dependent for characterizing the growth of the S-shaped diffusion process, which is consistent with the argument by Wu and Chu [6].

5. Conclusion

This paper has addressed the usefulness of two S-shaped diffusion models and two non-linear regression models to represent the life cycle after-market release of a new mobile phone adequately. Generally, because the curve of cumulative sales data

is the S-shaped curve and non-linear curve, we use the S-shaped diffusion and non-linear regression to fit the data to a model.

We compared the fitting abilities of four conventional diffusion models, the Gompertz, logistic, Michaelis-Menten, and logarithmic models over the life of the diffusion curve generate by analyzing 31 mobile phone sales data of one mobile operators in Korea for 18 months from March of 2013 to August of 2014. We find that the S-shaped diffusion models are more reliable than the non-linear regression models. Among four diffusion models, the logistic model outperforms the other models for the fitting of the observed data of 31 mobile phones.

Next, to forecast the trend curve of the cumulative sales data of new mobile phone, the two S-shaped diffusion models, the Gompertz and logistic models, are studied. Experimental results indicate that logistic model normally outperforms the Gompertz model considering the total product life cycle. However, logistic model outperforms the Gompertz model for the period prior to diffusion saturation, whereas the Gompertz model is superior after saturation approaches. Through the results from the two S-shaped diffusion models, we conclude that the appropriate diffusion model can be stage-dependent, and no single diffusion model is suited to all processes.

In this study, we knew that the life cycle of mobile phone tends to be shortened, and we may conclude that the shortened life cycle of mobile phone put pressure on stakeholders of mobile phone market to launch as quickly as possible and to predict inventory as optimally as possible. In summary, the S-shaped diffusion models are suitable to analyze the mobile market.

For future works, other technological forecasting techniques could be performed to forecast mobile phone sales and compared with the one studies in this research and evaluated accordingly. Also numerous longitudinal mobile phone sales cases could be used to develop a concrete rule for model selection during the S-shaped life span.

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