DIFFUSION AND FORECAST OF MOBILE SERVICE GENERATIONS IN GERMANY, UK, FRANCE AND ITALY – A COMPARATIVE ANALYSIS BASED ON BASS, GOMPERTZ AND SIMPLE LOGISTIC GROWTH MODELS

Research paper

Jha, Ashutosh, Management Information Systems Group, Indian Institute of Management Calcutta, Kolkata, India, ashutoshj14@iimcal.ac.in

Saha, Debashis, Management Information Systems Group, Indian Institute of Management Calcutta, Kolkata, India, ds@iimcal.ac.in

Abstract

Growth models, based on the theory of diffusion of innovations, are highly proficient in developing an empirical understanding of country-wide diffusion of mobile services. The currently available literature lacks in explanation of the diffusion of successive generations (G's) of mobile services in various countries. This study furthers the research by analyzing the diffusion of 2G through 4G in Germany, UK, France and Italy, the four largest economies of Europe. We select Bass, Gompertz and Simple Logistic growth models, to analyze the diffusion process, and forecast the adoption of 3G, 4G and 5G mobile broadband, in the four countries. A comparative analysis of the diffusion model parameters, and the forecasting accuracies, estimated through non-linear least-square regression, determines Gompertz and Simple Logistic model as best suited to explain 3G and 4G diffusion, and Bass model as best suited to explain 2G diffusion. Market potential for 3G, 4G and 5G is the highest in France, Germany and Italy, respectively. However, subscribers are more likely to make a direct jump from 2G to 4G in Italy and Germany, compared to UK and France where the gradual switch from 3G to 4G to 5G is likely to be much slower.

Keywords: Diffusion, Adoption, Mobile Generations, Bass Model, Gompertz Model, Simple Logistic Model.

1 Introduction

In the contemporary world, the field of wireless communications has established its ubiquity in multiple dimensions of human-to-human, human-to-machine, and machine-to-machine interactions (Zuboff, 1988). The advent of mobile phones has helped in the rapid proliferation of such wireless networks. Several innovation theorists consider mobile phones to be the most disruptive wireless communication device in the history considering its potential to stir up societies and economies (Jeffrey & Doron, 2013). With the progress in the miniaturization of computing devices and platforms, the initially simple and voice-centric mobile phones have undergone remarkable change, incorporating data connectivity and enabling access to the Internet over the mobile. This progress is a result of multiple paradigm shifts that have taken place in the wireless communication technologies and various networking standards used in the provisioning the mobile services (Xiang, Zheng, & Shen, 2017). Each of these shifts is conventionally labeled as a 'generation' (G), giving rise to the first (1G), second (2G), third (3G), fourth (4G) and fifth (5G) generation of mobile services, launched one after the other. Specifically, the mobile service generations from 2G onwards, i.e., 3G, 4G and 5G, are of special interest to us in this study, considering the shift – voice to data – they have brought, both in nature and the use of the mobile phones. These data-centric mobile service generations are, together, commonly referred to as the mobile broadband services – posited by the International Telecommunication Union (ITU) as “the fastest growing ICT in human history” (ITU, 2016).

Several studies predict that the global data traffic is likely to increase by more than 20000 times between the year 2010 to 2030, along with the rise in connected devices and the emergence of newer services therefrom (Xiang et al., 2017). The unprecedented growth in data traffic volume, network connectivity and deployment use cases, are currently being tackled by the telecom operators through provisioning services over 3G and 4G mobile broadband networks (Gupta & Jha, 2015). The 4G services, owing to their technical superiority over the predecessor technologies such as 3G, are currently utilized to meet the consumer demand for data. However, due to the impending challenges of newer usage scenarios in future, viz., Massive Machine-type Communications, Ultra-reliable and Low-Latency Communications, and Enhanced Mobile Broadband, 5G will need to take over the stage (Akyildiz, Nie, Lin, & Chandrasekaran, 2016). The telecommunications standards for 5G mobile networks (IMT-2020) are, therefore, currently being finalized by the International Telecommunications Union (ITU), with a view to rolling out the first set of services by the year 2020 (Ancans, Bobrovs, Ancans, & Kalibatiene, 2017). It is, therefore, not surprising that several countries, such as the United States, China, Japan, South-Korea and Sweden, to name a few, are aligning roadmaps and priorities for coordinated 5G deployment in the near future. In Europe, the European Commission has recently released its “5G Action Plan”, which targets early network introduction by 2018 and commercial large-scale introduction by the end of 2020, for all member states (EPRS, 2017).

Given this backdrop, a deeper understanding of the diffusion phenomena of these mobile service generations, at the country level, will serve the interests of all the stakeholders involved, especially the policymakers and the mobile network operators. Of special interest to these stakeholders will be the estimates of the ultimate market potential of each generation, the periods with increasing and decreasing rate of diffusion and the time to market saturation. In order to estimate the values of these important decision variables, previous researchers have taken help of various mathematical models belonging to the paradigm of Rogers’ theory of Diffusion of Innovations (DOI) (Rogers, 2010). The DOI-based empirical models, also referred to as growth models, have been utilized for explaining and predicting the diffusion of innovations, such as 2G and 3G, through a regression-based estimation of the model parameters which are then used for forecasting (Meade & Islam, 1995). In most of the prior studies on mobile service diffusion, three models, namely Bass, Gompertz and Simple Logistic, have been very frequently applied. This is due to the unique ability of each of these models to explain the diffusion process without the need for any exogenous decision variables (Sultanov et al., 2016; Ovando et al., 2015; Zhu et al., 2014; Naseri and Elliott, 2013; Turk and Trkman, 2012; Liu et al., 2012; Gupta and Jain, 2012; Wong et al., 2011; Bass, Krishnan, & Jain, 1994). This popularity is also generally ascribed to their simplicity and relative success in explaining the market adoption trend of a large range of innovations (Bass et al., 1994). In general, these models are utilized in a comparative manner, and the model which best fits the historical data of adoption is subsequently used for forecasting the future uptake of the innovation. The reason for comparative evaluation is due to the generally accepted notion that no particular model is best suited for forecasting all innovations for all contexts, given that the models are found to be highly sensitive to the available dataset (Sultan, Farley, & Lehmann, 1990).

We, in this study, attempt to further the research related to analyzing the diffusion and forecasting of mobile service generations in the four largest economies of Europe, namely Germany, UK, France and Italy. The diffusion analysis is performed for the case of 2G, 3G and 4G mobile services, while the forecasting is undertaken for the mobile broadband generations of 3G, 4G and 5G. The 3G and 4G services were launched in various European countries between years 2003-04 and 2010-12, respectively. Interestingly, the early market adoption trend of both 3G and 4G vary considerably, across the different countries in Europe, with 3G performing relatively better in certain countries when compared to 4G, and vice versa (Xiang et al., 2017). Overall, while 2G services have begun to reach market saturation, 3G and 4G are in the early stages of their adoption cycle in various European countries. The case of the four European countries chosen for analysis is pertinent given that most of the previous research on diffusion of mobile service generations, have remained restricted to analyzing the country level diffusion of early mobile telephony, i.e., 2G, and evaluating the influence of certain exogenous variables in diffusion (Gruber, 2001; Gruber and Verboven, 2001; Frank, 2004; Massini, 2004; Gamboa and Otero, 2009). Also, to the best of our knowledge, no prior study has undertaken the diffusion analysis and forecasting exercise of 3G, 4G and 5G services for any of the European countries, although few studies have analyzed the diffusion of 3G and pre-4G services for some of the Asian countries (Chu & Pan, 2008; Yates et al., 2013; Lee et al., 2011; Shin et al., 2015). The four countries chosen for analysis are also the four largest economies in Europe having the considerable presence of the majority of the mobile network operators functioning in the continent. The implications for the findings, for both telecom operators as well as the policymakers, are, therefore, considerable.

Our work contributes to the relevant literature in four ways. *Firstly*, we demonstrate the use of Bass, Gompertz and Simple Logistic growth models to explain the diffusion of 2G, 3G and 4G, in each country; we showcase how to evaluate the parameters of the diffusion process with the help of non-linear least-squares (NLS) regression technique. *Secondly*, we compare the NLS estimates of each diffusion model to determine their suitability towards explaining the diffusion process of each mobile service generation and evaluate the best-fit model for each generation. *Thirdly*, for each mobile service generation, we theorize the country-wise implications in detail, based on the levels of the estimated model parameters. *Fourthly*, and finally, we determine the forecasting capability of each model, for all mobile service generations, and utilize the most appropriate model to forecast the potential adoption of 3G, 4G and 5G services in the countries of Germany, UK, France and Italy.

The remainder of this paper is structured as follows. Section 2 provides an overview of the background and related literature and therefrom draws upon our research objectives. In Section 3, we provide the theoretical overview of the chosen models. In Section 4 we highlight our research methodology, providing detailed explanations of various steps undertaken. In Section 5, we provide the details on the dataset used, the initial input values in the NLS estimations, and the subsequent results. Finally, Section 6 concludes with our findings and identifies the implications for praxis.

2 Background and Related Work

In this section, we provide a brief overview of: a) mobile telephony generations in Germany, UK, France and Italy, and b) the previous research works that have empirically studied the diffusion of various innovations in different regions of the world. A vast amount of innovation types have been studied using the mathematical models of diffusion, thereby, making the exhaustive review of the works a challenging endeavor, more so given the space constraints in this paper. We, therefore, provide a focused review of pertinent works that have studied the diffusion phenomena of mobile services only. We also introduce, in addition, the related literature coherent with various modeling approaches undertaken. We then summarize the research gaps and propose our extensions.

2.1 Mobile Service Generations in Germany, UK, France and Italy

As mentioned previously, the technology and infrastructure i.e., the communication networks and the device ecosystems enabling the mobile services, have been found to undergo a paradigm shift after each decade (Pagani & Fine, 2008). These shifts result in newer services, newer transmission technologies, higher data rates, and use of newer frequency bands (Pagani & Fine, 2008). We summarize in Table 1, these technological characteristics of 2G, 3G and 4G mobile services, while Figure 1 depicts their individual historical trajectories of growth, in the countries of Germany, France, UK and Italy, respectively.

It is evident from the preliminary examination that while the diffusion of 2G seems to have been successful in all the chosen countries, both 3G and 4G are currently in the early phase of the adoption curve – at least in Germany, France and Italy. Interestingly, 4G uptake seems to be more successful in the UK when compared to 3G, while the reverse is true for Italy.

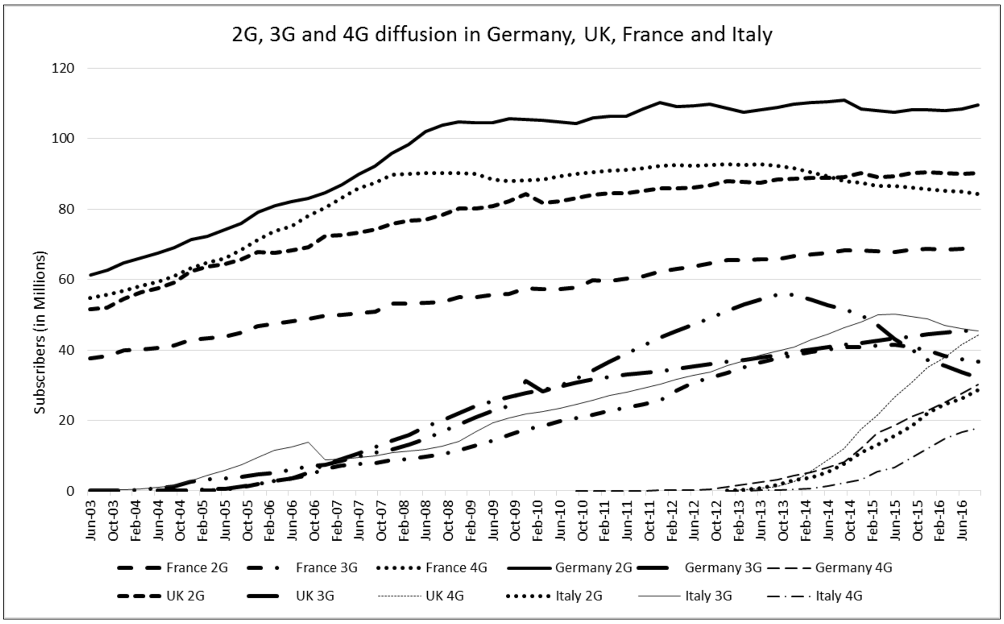


Figure 1: Diffusion of 2G, 3G and 4G in Germany, UK, France and Italy

		Germany	France	UK	Italy
Subscribers (million)	2G	109.54	69.28	90.21	84.31
	3G	45.70	36.68	32.08	45.49
	4G	30.23	28.7	44.35	17.85
Year of roll-out	2G	1992	1994	1994	1994
	3G	2004	2004	2003	2003
	4G	2010	2012	2012	2012
Features	2G	Digital Voice Communication, Short Message Services (SMS)			
	3G	Internet-enabled, Video Communication, Live podcast			
	4G	Ultra-Broadband, Higher data capacity, IP-oriented, Multimedia services			
Telecom Operators	2G	Vodafone, O2, Telekom	Orange, SFR, Bouygues Telecom, Free Mobile	EE, O2, Vodafone, Three	Wind Tre, TIM, Vodafone
	3G				
	4G				
Speed	2G	9.6 – 172 Kbps			
	3G	382 Kbps – 2 Mbps			
	4G	86 – 326 Mbps			

Data Source: TeleGeography and Business Monitor International databases. Subscriber data as on September, 2016.

Table 1: 2G, 3G and 4G mobile service in Germany, France, UK and Italy

2.2 Diffusion of Mobile Service Generations

The theory of DOI was initially propounded by Everett Rogers wherein he explained the dynamics of spread and adoption of new ideas and technologies, by the members – known as potential adopters – in a given social system (Rogers, 2010). The theory has, since then, given rise to several mathematical models some of which have become the most widely used models, such as the Bass model (Bass, 1969), the Gompertz model (Franses, 1994) and the Simple Logistic model (Meade & Islam, 1995). These models help reveal, mathematically, the marketing and behavioral influences of the main drivers of the diffusion process, namely word-of-mouth, consumer interactions, signaling and interpersonal communications, social networks, positive externalities and the role of advertising and marketing (Peres, Muller, & Mahajan, 2010). The models also help understand the adoption of newly launched products, services and innovations at different levels of analysis, including individual, organizational and societal (Dodson & Muller, 1978). Not surprisingly then, these and several other DOI models continue to get utilized for understanding the spread of innovations belonging to several domains, ranging from agricultural science (e.g. hybrid corn), corporate finance (e.g. financial investments), marketing (e.g. consumer durable goods) to several other industrial innovations (e.g. IBM Mainframes, IPTV etc.) (Fareena, Farley, & Lehmann, 1990; S. Lee, Park, Lee, & Brown, 2015). Specific to the diffusion of mobile service generations, namely 2G, 3G and 4G, previous research works have frequently utilized these models for understanding aspects of the diffusion process in many regions of the world. However, majority of research remains focused around studying the diffusion of 2G (Gruber, 2001; Gruber and Verboven, 2001; Frank, 2004; Wareham et al., 2004; Massini, 2004; Koski and Kretschmer, 2005; Rouvinen, 2006; Lee and Cho, 2007; Gamboa and Otero, 2009; Hwang et al., 2009; Liu et al., 2012; Gupta & Jain, 2012; Yamakawa et al., 2013; Sultanov et al., 2016), owing mostly to the availability of the market adoption data which is scarce for 3G and 4G.

Gruber (2001), for example, highlights, with the help of Gompertz and Logistic-based models, that the countries belonging to the central and the eastern-Europe that are late adopters of 2G mobile services have higher diffusion speed when compared to countries where the innovation was initially deployed. Gruber (2001) also utilizes the Gompertz and Logistic-based models in order to estimate the influence of external variables such as income, fixed-line subscriptions, level of urbanization, the extent of country's transition into the market economy and entry of firms, on the diffusion speed of 2G. In another work, Massini (2004) utilizes the Gompertz and Logistic models to understand the diffusion patterns of 2G in UK and Italy, and the influence of various technological and economic factors on the speed of diffusion. Interestingly, Massini (2004) finds that the same external factors affect the speed of diffusion in totally opposing ways in UK and Italy. In another work of importance, Frank (2004) utilizes the Logistic model to forecast the adoption of 2G services in Finland and evaluates the factors that affect the diffusion process in the country. The study by Frank (2004) also explains in detail the role played by the prevailing economic situation on the growth rate of 2G diffusion, as well as the influence of the extent of wireless network coverage on the number of potential adopters of 2G. As far as utilizing the diffusion models in a comparative manner, for determining the best-suited model for forecasting purposes, is concerned, several studies do exist in the literature. Lee and Cho (2007), for example, have compared the performance of the Logistic model with that of a time-series autoregressive moving average (ARMA) model for diffusion of 2G in Korea. Michalakelis, Varoutas and Sphicopoulos (2008) have compared the performance of both the basic and the extended versions of Bass, Gompertz and Logistic models, to explain the diffusion of 2G in Greece. The study by Michalakelis, Varoutas and Sphicopoulos (2008) offers interesting insights, highlighting the variability of the model fitness with the dataset at hand and the difference in model predictions about the ultimate market potential scenarios – optimistic, moderate and conservative.

As compared to 2G, fewer research works have undertaken the analysis of 3G (Chu & Pan, 2008; Abu, 2010; Yates et al., 2013; Lee et al., 2011; Shin et al., 2015) and 4G (Xia, 2012; Tseng et al., 2014) diffusion, while no study in literature exists, to the best of our knowledge, on the diffusion analysis of 5G. Of the notable works on 3G, Chu and Pan (2008) in their study, evaluate the diffusion of mobile internet and forecast its market growth for the country of Taiwan. Chu and Pan (2008) highlight in a comparative manner, the effects of *technological substitution* and *multi-product competition* on the diffusion of 2G and 3G in Taiwan. The study utilized Bass model and the extended versions of the Bass model for the analysis. The study by Shin and Koh (2010) attempts to explain the diffusion of mobile broadband services in South Korea with the help of a framework based on the theory of DOI. Lee, Kim and Cho (2011) have utilized the Logistic model to evaluate the effects of technology diffusion on the spillovers of technology, using the patent citation data of Code Division Multiple Access (CDMA), a 3G technology, in South Korea. While studies on 4G adoption do exist in literature, they remain restricted to providing a theoretical framework based explanations of the 4G adoption, focusing around the mechanisms of market behaviors i.e., competition development, technology development, industry structure and regulatory imperatives – for example, the study on 4G in China by Xia (2010), and on 4G in Taiwan by Tseng, Wang, Hsieh and Guo (2014). No extensive use of diffusion models has been undertaken in the above-mentioned works.

3 Overview of Bass, Gompertz and Simple Logistic Models

There exists a wide range of mathematical models for analyzing the diffusion of newer innovations through empirical estimation of the diffusion parameters, which are then used for forecasting the market adoption of the innovation. As mentioned earlier, of these available models, Bass, Gompertz and Simple Logistic are the most commonly applied, especially in the studies concerning the diffusion of ICT innovations (Sultanov et al., 2016; Ovando et al., 2015; Zhu et al., 2014; Naseri and Elliott, 2013; Turk and Trkman, 2012; Liu et al., 2012; Gupta and Jain, 2012; Wong et al., 2011). Table 2 summarizes the model equations that are utilized in the empirical analysis pertaining to all the NLS regression estimations and subsequent forecasting.

Diffusion Model	**Bass**	**Gompertz**	**Simple Logistic**
Model Equation $\frac{dF(t)}{dt} =$	$(p + qF(t))\,(1 - F(t))$	$b_1 ln\frac{K}{F}$	$b_1\left(1 - \frac{F}{K}\right)$
Model Solution $F(t) =$	$M\left[\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}\right]$	$Ke^{-e^{-b_1(t-b_2)}}$	$\left[\frac{K}{1 + e^{-b_1(t-b_2)}}\right]$

$F(t)$ = the cumulative adoption till time t; *K/M* = market potential (the number of adopters in equilibrium or saturation level); $f(t)$ = likelihood of adoption at time t; p = coefficient of innovation; q = coefficient of imitation; b_1= speed of diffusion (intrinsic rate of growth); b_2= positive parameter used as an offset.

Table 2: The diffusion models used for comparative estimation and forecasting

The Bass model was initially developed to forecast the product sales in marketing (Bass, 1969). The model was based on the rationale of Roger's theory of DOI (Rogers, 2010). Unlike Rogers', Bass categorized the entire set of potential adopters into *innovators* –information gatherers using formal channels of communication – and *imitators* – information gatherers through informal channels of communication (Bass, 1969). In the Bass model, the coefficient of innovation (p) captures the probability of an initial purchase during the beginning of the product's life cycle and is directly related to the initial critical mass of the adopters, i.e., the *innovators* (Michalakelis, Varoutas, & Sphicopoulos, 2008). This factor highly influences the rest of the diffusion process, especially the *imitators,* who constitute the remaining population that are yet to adopt the innovation (Michalakelis et al., 2008). The dynamics behind the imitative behavior involved in the adoption process gets captured by the coefficient of imitation (q).

The Gompertz model was proposed by the Jewish mathematician Benjamin Gompertz and has been used in fitting and forecasting of time series processes, such as the sales of a new product or innovation (Franses, 1994). The two main characteristics of the Gompertz curve are: a) the occurrence of the *point of inflection*, which represents the time in the diffusion process when the rate of growth of the diffusion changes from increasing to decreasing, even before half of the saturation is reached, and b) the non-negative rate of growth, in spite of exhibiting a decrease over time (Franses, 1994). The Simple Logistic growth-based model, on the other hand, was proposed by the Belgian mathematician Pierre Francois Verhulst and it was meant for demographic studies (Nguimkeu, 2014). The model was based on the rationale of slowing down of growth as the population approached its uppermost limit, essentially due to the feedback information of limits on the system (Berger, 1981). The parameters in the Simple Logistic growth model have similar implications as that of the Gompertz model.

4 Research Methodology

The methodology followed in the paper – summarized in Figure 2 – has three major components. We explain in detail in the subsequent sections, the individual analysis steps under each component.

The quarterly adoption data of 2G, 3G and 4G mobile services are collected for the countries of France, UK, Germany and Italy, to begin with. As previously mentioned, we utilize the three growth models, namely Bass, Gompertz and Simple Logistic, to analyze the diffusion of 2G, 3G and 4G in these countries. Since the chosen models are non-linear models, we perform NLS regression estimation on the adoption data set of each mobile service generation, across all the countries. The initial values of the diffusion parameters, specified in the NLS regression, are obtained through the ordinary least-squares (OLS) estimation of Bass model, the details of which we do not provide for the sake of brevity and also considering that this is a fairly standard approach utilized in several other works as well (Bass, 1969; Srinivasan and Mason, 1986).

The estimated diffusion model parameters from the previous step, are compared with each other in terms of their power to explain the diffusion of 2G, 3G and 4G mobile services. We chose the *Adjusted R^2* and the *Root Mean Square Error (RMSE)* as the indicators measuring model robustness and fit, as also established by the prior literature (Srinivasan and Mason, 1986). The Adjusted R^2 indicator evaluates, statistically, the closeness of the real data to the fitted regression line, whereas RMSE represents the difference between values predicted by a model, or an estimator, and the values actually observed. Amongst these two indicators, RMSE is considered to be a better metric given the importance of achieving lower standard errors in the model-fitting exercise (Tsai, 2013). Only those parameter values, which conform to the normative requirements pertaining to the specified convergence criteria, sign, and magnitude, are accepted for final interpretation. The specific implications pertaining to the behavioral dynamics behind the adoption of the innovation under examination and its characteristics, such as speed of diffusion, etc. are explained, therefrom.

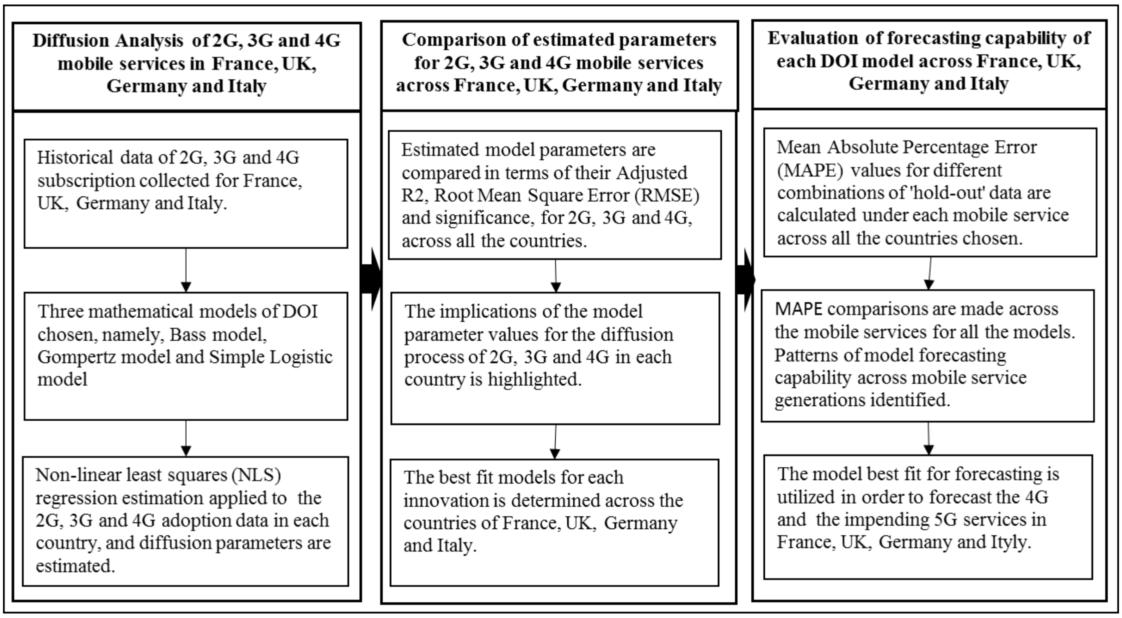


Figure 2: Summary of steps in the analysis

However, the model best-fit to the historical data need not necessarily be the model with the better forecasting capability (Meade & Islam, 1995). We, therefore, evaluate the forecasting capability of each model – for 2G, 3G and 4G, in the chosen countries – by comparing the forecasted values under a given time horizon with the known samples from historical data (known as the *hold-back* data) for the same horizon. Towards this, we calculate the Mean Absolute Percentage Error (MAPE) indicator, which is used as the measure of forecasting performance. MAPE is calculated as shown below:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{|x_i - \hat{x}_i|}{\hat{x}_i}$$

where x_i is the actual value at time t, $\hat{x}_i$ is the forecasted value at time t, and n is the number of observations. These measurements depend on the residuals - representing the deviation between the real data and the predicted data. Consequently, smaller values of these measurements suggest the fitness and acceptability of the forecasting performance. The best fit model according to the MAPE criterion is chosen for forecasting the 4G and 5G adoption in the countries of France, UK, Germany and Italy.

5 Data Sources and Evaluation Results

The secondary data used in the analysis were collected from multiple sources, namely the Organisation for Economic Co-operation and Development (OECD) database (OECD, 2017), GlobalComms database service of TeleGeography (TeleGeography, 2017), and Business Monitor International Research database (BMI Research, 2017). For the NLS estimation of diffusion model parameters, we make use of the statistical software package STATA, while the forecasting exercise is done over the R-Studio platform using the 'Growth-Models' package available in the Comprehensive R Archive Network (CRAN). The time horizons of the utilized historical subscription data for 2G, 3G and 4G, in each of the countries, are mentioned in Table 3 below.

	Germany	**UK**	**France**	**Italy**
2G	Q2, 2003 – Q3, 2016	Q2, 2003 – Q3, 2016	Q2, 2003 – Q3, 2016	Q2, 2003 – Q3, 2016
3G	Q2. 2004 – Q3, 2016	Q2, 2003 – Q3, 2016	Q2, 2004 – Q3, 2016	Q2, 2003 – Q3, 2016
4G	Q3, 2010 – Q3, 2016	Q4, 2012 – Q3, 2016	Q3, 2010 – Q3, 2016	Q4, 2012 – Q3, 2016

Table 3: Time-duration of the quarterly (Q) sample data used in the analysis

5.1 Parameter Estimation Results and Model Selection

We apply the NLS regression estimation technique, over the historical data of 2G, 3G and 4G subscription in Germany, UK, France and Italy, and estimate the diffusion parameters of Bass (M, p and q), Gompertz (K, b_1 and b_2) and Simple Logistic (K, $b_1$and b_2) models. The results of the analysis, for the four chosen countries and across the three mobile service generations, namely 2G, 3G and 4G, have been summarized in Table 4, 5 and 6, respectively.

		M / K	p **/** b_1	q **/** b_2	**Adj. R^2**	**RMSE**
France	Bass	7.99E+07	0.00594	0.030682	0.9999	694744
	Gompertz	5.58E+07	-10.1537	104.3696	0.9708	10100000
	Simple Logistic	5.28E+07	-13.2054	104.0865	0.9619	11200000.0
UK	Bass	9.18E+07	0.002640	0.068797	0.9999	686750
	Gompertz	9.28E+07	0.060388	41.47854	0.9999	670558
	Simple Logistic	9.17E+07	0.072638	46.55788	0.9999	691389
Germany	Bass	1.11E+08	0.000840	0.094706	0.9993	2519684
	Gompertz*	9.65E+07	-14.6856	76240.12	0.00E+00	16000000
		4.60e+07	0.1481217	60.95164	0.9891	1664946
	Simple Logistic	1.11E+08	0.095785	49.61613	0.9993	2512474
Italy	Bass	9.73E+09	0.000185	-0.01636	0.9881	9118325
	Gompertz	9.08E+07	0.119148	46.14725	0.9984	3380860

	Simple Logistic*	8.27E+07	-0.213110	441.5296	0.00	11700000
		4.97e+07	0.1944943	62.74688	0.9917	1456077

Table 4: 2G diffusion – NLS estimation results

		M / K	p / b_1	q / b_2	**Adj. R²**	**RMSE**
France	Bass	4.33E+07	0.004569	0.124276	0.9959	1623107
	Gompertz	4.27E+07	0.141010	26.08709	0.9959	1630295
	Simple Logistic	4.79E+07	0.076780	22.8434	0.9944	1901461
UK	Bass	4.73E+07	0.001312	0.203443	0.9750	5146500
	Gompertz	4.81E+07	0.139898	21.53091	0.9702	5616858
	Simple Logistic	4.74E+07	0.205367	24.71797	0.9752	5126890
Germany	Bass	1.55E+10	0.007560	-0.007820	0.9895	3061770
	Gompertz	4.48E+07	0.101469	16.54364	0.9982	1248946
	Simple Logistic	4.24E+07	0.163152	19.88119	0.9953	2040928
Italy	Bass	6.21E+07	0.005897	0.069169	0.9940	2218470
	Gompertz	7.48E+07	0.044460	32.09627	0.9934	2316820
	Simple Logistic	5.63E+07	0.097127	32.67167	0.9940	2209525

Table 5: 3G diffusion – NLS estimation results

		M / K	p / b_1	q / b_2	**Adj. R²**	**RMSE**
France	Bass	3.39E+07	0.006651	0.344191	0.9993	388296.0
	Gompertz	4.47E+07	0.170680	11.18476	0.9994	356125.3
	Simple Logistic	3.25E+07	0.385280	11.10850	0.9989	501301.4
UK	Bass	4.73E+07	0.004881	0.424743	0.9991	726207.1
	Gompertz	5.61E+07	0.228406	9.751427	0.9999	289346.3
	Simple Logistic	4.65E+07	0.453651	10.36271	0.9987	857386.7
Germany	Bass	3.38E+07	0.000326	0.355956	0.9981	567589.9
	Gompertz	4.88E+07	0.150144	20.08879	0.9973	679815.5
	Simple Logistic	3.37E+07	0.358283	19.62286	0.9981	568473.5
Italy	Bass	2.09E+07	0.001023	0.501465	0.9994	212171.8
	Gompertz	2.92E+07	0.218546	12.48951	0.9982	360751.2
	Simple Logistic	2.08E+07	0.507715	12.31844	0.9994	212159.0

Table 6: 4G diffusion – NLS estimation results

The results of the NLS regression suggest the general suitability and sufficiency of all the three growth models towards explaining the prior adoption of the three mobile service generations, across all the four countries. This is evident from the high values of their Adjusted R^2 – the metric used to evaluate the model fitness criteria by several prior studies (Tsai, 2013). Except for the parameters in the cells highlighted in grey in Tables 4, 5 and 6, all the other parameters are very highly significant (p-value < 0.001) in the diffusion process. The NLS estimation procedure failed to achieve the convergence criteria even after thousands of iterations, for the rows containing the cells highlighted in grey, for Gompertz and Simple Logistic models marked with asterisks (*). An intercept term was added to the models to account for the initial subscription and the NLS estimation was reapplied. The results of the second set of estimations are mentioned in the in the new row below the highlighted cells. The cells in grey, for the case of Bass model, represent the non-significance of the particular diffusion model parameter.

As far as the *ultimate market potential (M/K)* estimates are concerned, we can infer from Tables 4, 5 and 6 that the Bass model yields the most optimistic estimate for 2G, whereas, for 3G and 4G, the Gompertz model estimates are the most optimistic. The Simple Logistic estimates of the ultimate market potential remain conservative across all the mobile service generations. This particular result offers an interesting insight into the capabilities of the growth-models to explain, both, the short-term diffusion process of newer innovations (for example, 3G and 4G) in the early growth stage, as well as the long-term diffusion process of older innovations whose growth-curves have crossed the inflection-point and are approaching saturation. Based on the estimates of the ultimate market potential (M/K) reported in Tables 4, 5 and 6, Bass model most certainly qualifies to explain well the diffusion process of innovations falling in the latter category, whereas Gompertz model is suited to the innovations in the former category.

In terms of the model best fit to explain the adoption dynamics of 2G, 3G and 4G, the following could be observed after taking into account the Adjusted R^2, RMSE and the feasible ultimate market potential estimates: a) Bass model best fits the 2G diffusion in both France and Germany, 3G diffusion in France, and 4G diffusion in Germany, b) Gompertz model best fits the 2G diffusion in the UK, 3G diffusion in Germany, and 4G diffusion in both France and the UK, and c) Simple Logistic model best fits the 2G diffusion in Italy, and both 3G and 4G diffusion in UK and Italy, respectively. It is clear from the results that when it comes to explaining the diffusion of the mobile service generations in the four chosen countries, no model is superior to the other model in all the cases. Also, since in some of the cases, the modeling failed to achieve the convergence criteria even after multiple iterations, the values of the indicators could not be used for comparison purposes. Therefore, to make any generic claims regarding the best-fit model for 2G, 3G and 4G diffusion in all the cases may lead to inconsistencies. We, therefore, take help of the accuracy of the forecasts generated by each model for establishing their relative suitability for representing the diffusion process of the mobile service generations in the chosen countries, in the next section.

5.2 Forecasting Performance Evaluation Results

To evaluate the forecasting accuracies of each of the three chosen models, we first segregate a portion of the last known data points from the overall historical data and keep aside as the ‘hold-out’ data. We then forecast the subscriber adoption figures, over the same period as the hold-out data, using the NLS determined coefficients of the growth models. Finally, the MAPE values are evaluated for the corresponding periods, by comparing the forecasted values with the real subscriber adoption values, as also explained in section 4. The MAPE indictor thus obtained, helps in establishing the forecasting capabilities – both the long and the short-term – of the models, in a highly rigorous manner.

	2G			**3G**			**4G**		
	Bass	Gompertz	Simple Logistic	Bass	Gompertz	Simple Logistic	Bass	Gompertz	Simple Logistic
MAPE4	44.15	18.91	23.27	6.61	6.40	8.49	2.71	33.75	2.91
MAPE6	45.22	18.62	22.99	5.90	5.71	6.84	3.08	31.65	3.77
MAPE8	46.43	18.53	22.91	5.77	5.53	6.21	2.98	30.39	4.00
MAPE10	47.54	18.26	22.66	5.79	5.50	5.90	2.92	31.93	3.56
MAPE15	50.25	17.35	21.80	5.20	4.76	4.73	3.00	31.32	3.78

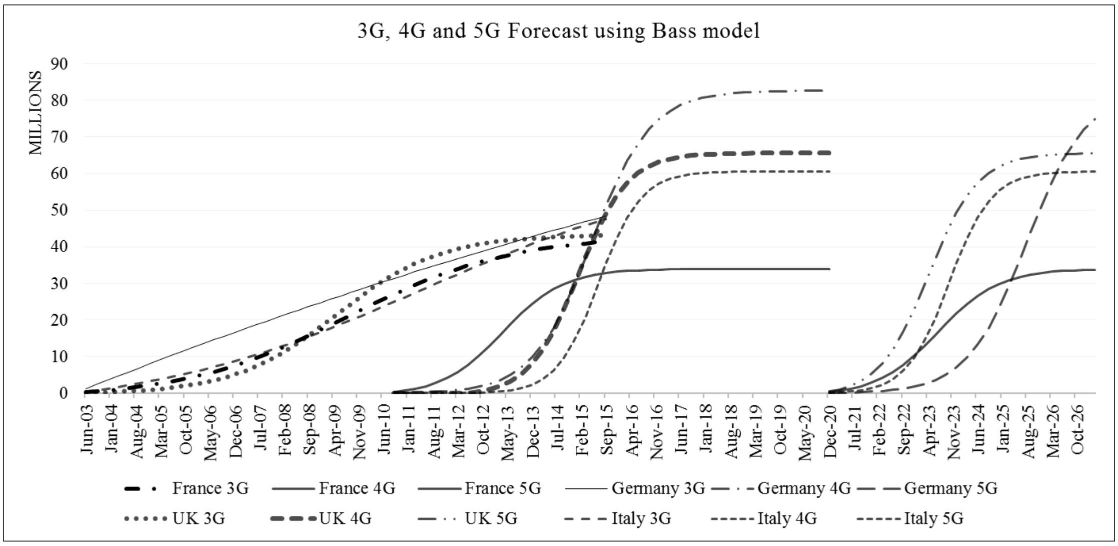
Table 7: MAPE (%) for different hold-out periods (representative case of France, only)

The results of the MAPE calculations are summarized in Table 7. We have chosen 5 scenarios with varying hold-out periods consisting of 4 (MAPE4), 6 (MAPE6), 8 (MAPE8), 10 (MAPE10) and 15 (MAPE15) quarters, respectively. In Table 7, we have only shown the results for France due to the page limit constraints of the article. However, the other countries also display a very similar trend.

Regarding the forecasting performance of the models, we can observe from Table 7 that the performance for Bass and Simple Logistic models increase significantly between 2G to 3G and subsequently for 4G. However, the same deteriorates for the Gompertz model, which seems to be much poorer in forecasting the 4G subscription, across all the countries. This points to the effectiveness of the Bass and Simple Logistic models towards closely capturing the early adoption trend of an innovation (Bass et al., 1994). Considering that the Bass model overestimates the cumulative adoption (as is evident from the large M values generated in Tables 4, 5 and 6) towards the end of diffusion, i.e., the phase when saturation starts setting in the innovation growth curve, we posit its suitability in predicting the early adoption of an innovation. The Simple Logistic model-based forecasts can serve as conservative estimates for both the short and the long-term adoption of the innovation.

5.3 Forecasting 3G, 4G and 5G Adoption in Germany, UK, France and Italy

In this section, we forecast the countrywide adoption of the mobile broadband services, namely 3G, 4G and the impending 5G, in the four chosen countries. As far as the forecast of yet to be introduced 5G is concerned, it is done with an underlying assumption that the adoption dynamics of 5G innovation, at the level of an individual, is likely to be very similar to that of 4G (Jha & Saha, 2018). The transition from 4G to 5G is taking place in the form of small incremental technological improvements in the wireless networks (Jha & Saha, 2018) such as Long-Term Evolution (LTE), LTE-Advanced, LTE-Advanced Pro, Massive MIMO, mmWave, etc. Also, for the network operators, making a switch from 4G to 5G is much easier now given the 5G-readiness of their 4G networks, unlike the highly costly affair of switching from 3G to 4G, earlier. This will mean a rapid phasing out of the legacy 4G network once 5G is launched, thereby initiating the 5G adoption process, which is likely to follow the path of 4G. We also assume that the subscribers of 5G services will mostly comprise of those migrating from 3G and 4G services. This is also pertinent given the fact that 5G services will be launched only post year 2020, by which time the 4G adoption curve will begin to saturate.



The forecast trend of 3G and 4G have not been extended until the later years in the above figure, due to clarity purposes. It should be noted that the adoption of 3G in all countries is saturated post year 2016, as is also clearly evident.

Figure 3: 4G and 5G adoption forecast in Germany, France, UK and Italy

Given that we are interested in the long-term country-wide adoption of 3G, 4G and 5G services in Germany, France, UK and Italy, we choose the Bass model for our forecasting exercise. Figure 3 captures the adoption forecast of 3G, 4G and 5G services after having accounted for the rise in population and accordingly specifying the ultimate market potential (M/K) of the two services, for each of the countries. The ultimate market potential of 3G, 4G and 5G services, as estimated by the chosen growth models, have been summarized in Table 8.

	3G (Million)	4G (Million)	5G (Million)
France	41.44	33.90	33.71
Germany	48.43	82.64	74.91
UK	43.06	65.60	65.52
Italy	47.57	60.60	60.54

Table 8: Estimate of Ultimate Market Potential of 3G, 4G and 5G services

6 Discussions

In this paper, we use the Bass, Gompertz and Simple Logistic growth models to estimate, with the help of non-linear least-squares regression, the diffusion parameters of 2G, 3G and 4G mobile services in the countries of France, UK, Germany and Italy. We discuss in this section, the theoretical and practical implications of the results generated in the earlier sections.

We can infer from the results of the NLS estimation obtained in section 5.1, that the value of the *coefficient of innovation* (p) is the highest in both France and UK, for 4G, followed by 2G and 3G. The same for Germany is 3G, followed by 2G and 4G. In contrast, the *coefficient of imitation* (q) values are the highest for 4G, followed by 3G and 2G, across all the countries. On the basis of these results, we posit that the introduction of 3G services resulted in the building of a higher critical mass of early adopters, i.e., the innovators, in both Germany and Italy, as compared to both 2G and 4G. This also reflects the effectiveness of the formal sources of communication, i.e., advertising and promotions, for 3G, in both Germany and Italy. This insight could be leveraged by the marketers in these countries, for both 4G as well as the impending 5G services, considering the fact that 4G is still in the early-growth phase in both Germany and Italy. For the countries of France and UK, the results suggest that the introduction of 4G was more successful in building the critical mass of early adopters, when compared to both 2G and 3G services. It is also evident that for 4G, the behavioural trait of imitativeness is highly influential, signifying considerable positive as well as negative impacts of word-of-mouth etc., on the final adoption.

The speed of diffusion (b_1) as estimated by the Gompertz model is slightly higher for 4G when compared to 3G, across all the countries. However, this gap in the speed of 3G and 4G diffusion increases when measured by the Simple Logistic model, which determines the speed of 4G diffusion to be greater than 3G across all the countries. The speed of 3G diffusion is the slowest in Italy, followed by Germany, UK and France, where it is the fastest. Similarly, the speed of diffusion of 4G is the slowest in Germany, followed by France, UK and Italy, where the diffusion is the fastest. This also signals poor adoption of 3G services in Italy and Germany when compared to UK and France, and the higher probability of 4G's success (in terms of subscriber adoption) in Italy and Germany, where the subscribers are more likely to make a direct switch from 2G to 4G.

It is evident from Table 8 that 3G services will oversee very similar ultimate market adoption in all the four countries in spite of their population differences. However, the early saturation period of 3G services across the countries, suggests the likelihood of 3G services getting substituted by 4G much earlier than expected, notwithstanding their better early uptake when compared to 4G in some countries. For the case of France the ultimate market adoption of 3G is higher than 4G and 5G, signaling the large build-up of *early-adopters* of 3G, who are likely to delay the switch from 3G to 4G, or 5G. The rate of diffusion of 4G and 5G services seems much higher in Germany, which is also corroborated by the healthy market potential figures of 4G and 5G

6.1 Theoretical and Practical Implications

This study contributes to the prior literature on diffusion of innovations by undertaking, for the first time, the analysis of the countrywide diffusion of mobile service generations, namely 2G, 3G and 4G, in the four largest economies of Europe, viz., Germany, UK, France, and Italy. The findings of the study, *firstly*, validate the existing understanding about the varying capabilities of the commonly used growth models, namely Bass, Gompertz and Simple Logistic, towards explaining the diffusion phenomena for mobile innovations along with their behavioral underpinnings (Bass et al., 1994; Mahajan, Muller, &

Bass, 2011). The unique role played by each innovation and the extent of availability of adoption data, towards moderating the model fitness criteria, forecasting performance and the speed of diffusion, for each of the chosen models, are also highlighted in the study (Naseri & Elliott, 2013). *Secondly,* the study contributes to the scarcely available literature targeted at understanding the diffusion phenomena of multiple product generations, in a given country. The comparative evaluation undertaken, through highlighting the differences in the diffusion parameters, generate several cross-country insights. *Thirdly*, for the case of mobile service generations, the study finds the overall duration, i.e., from inception to the saturation, of the adoption lifecycle of mobile service generations to comprise of 8-10 years.

In terms of practical implications, the variables such as the speed of diffusion, time taken in adoption and the ultimate market potential, for each country, can help the telecom operators plan their network deployments, technology upgrade and service provisioning, in a phased manner. This can lead to better planning of the required investments in the radio network infrastructure components such as radio spectrum. The behavioral insights offered by the Bass model parameters can also help marketers focus on the most effective communication channel in a given country, to increase the chances of adoption. For example, for the case of 4G, the Bass model parameters indicate higher *innovativeness* in the early-adopters in France. Therefore, the marketers can focus on the formal sources of communication to increase the chances of adoption in France. In contrast, for the case of Italy, the word-of-mouth plays a greater role in the final adoption, thereby needing a different marketing strategy. In a similar way, the country-specific insights can be helpful to the policymakers, which can lead to improved regulations targeted at accentuating the uptake of these mobile service generations.

6.2 Future Research and Limitations

This work, by its very nature, can only highlight the macro-level dynamics of diffusion for the chosen innovation generations. The future work would need to take into account various socio-economic, regulatory and technological factors into consideration, in order to probe further the impacts of the exogenous variables on the diffusion process. This is also pertinent in the light of the wide differences reported in the study, related to the adoption behaviour of the four chosen countries. A comparative evaluation amongst more such models would go a long way towards enriching the literature in this area.

7 Conclusion

This paper analyses the phenomena behind the country-wide diffusion of mobile service generations, namely 2G, 3G and 4G, in the four largest economies of Europe viz. Germany, UK, France and Italy. The diffusion analysis utilizes three growth models, namely Bass, Gompertz and Simple Logistic, and applies non-linear least-squares (NLS) regression technique to estimate the model parameters. We evaluate the models best suited to explain the diffusion phenomena under each mobile service generation and country combination. We also evaluate the forecasting capabilities of each model and utilize the most appropriate model to forecast the country-wide adoption of 3G, 4G and the impending 5G services, in Germany, UK, France and Italy, over a ten-year horizon. We find that the Bass model continues to remain suitable for explaining the long-term diffusion behaviour while predicting accurate short-term forecasts. Gompertz and Simple Logistic models, on the other hand, prove to be more useful in explaining the short-term diffusion behaviour of innovations in the early-growth stage and predicting long-term forecast, which range from extremely conservative to highly optimistic. A thorough analyses of the parameters measuring the speed of diffusion in each country reveals that the subscribers are more likely to make a direct jump from 2G to 4G in Italy as well as in Germany, compared to UK and France where the gradual switch from 3G to 4G and then to 5G is likely to be much slower. Our analysis also reveals that, compared to both 2G and 4G, the introduction of 3G services in both Germany and Italy resulted in the build-up of a higher critical-mass of early adopters (aka, the innovators). This behaviour signals that the formal sources of communication, i.e., advertising and promotions, have been more effective in Germany and Italy. In contrast, for both UK and France, the introduction of 4G services was more successful in building the critical mass of innovators, signaling the effectiveness of informal sources of communication, such as word-of-mouth and informal reviews, in these countries.

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