Serv Bus (2011) 5:155–172
DOI 10.1007/s11628-011-0108-8

Innovation and imitation effects in Metaverse service adoption

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Published online: 5 June 2011

Abstract This study examines the innovation and imitation effects in Metaverse service adoption. "Metaverse services" is a collective term for services such as Augmented reality, Life logging, Mirror world, and Virtual world. Among them, Twitter, Google, iPhone, and Secondlife (T.G.I.S) are the most popular services/products these days. To measure the adoption of these product/services, the most commonly used are IP traffic and iPhone sales. Thus, in this study, we measured adoption by measuring changes in the IP traffic volume of Twitter.com, Maps.Google.com, Secondlife.com, and sales for iPhone during a 2-year period (from the first quarter of 2008 to the fourth quarter of 2009). To analyze this time series data to reveal the innovation and imitation effect, we employed the Bass model. The results showed that each of these services yields different innovation and imitation coefficient values. Imitation effects for all Metaverse services are greater than innovation effects, and Secondlife's innovation effects are larger than others. Also, iPhone sales, as a measurement for information and communication technology (ICT) products, showed greater innovation effects than the other

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services. Implications are drawn to explain these differences, such as, Google-map's imitation effects are based on network externalities, while Twitter's imitation effects are caused by the interactions of individuals; iPhone sales' innovation effects are explained by the timing of the measurement.

Keywords Metaverse · iPhone · Bass model · Innovation · Imitation · Service adoption

1 Introduction

Not so long ago, when people started connecting to each other through a wired communication system, the Internet, it brought about a revolution in the rate of users' adoption of the technology involved. As wired technology has migrated to mobile technology, users could more easily communicate anywhere and at any time. Today, coupled with smart devices such as the personal digital assistant (PDA), laptops and smart phones, wireless technology is opening up the possibility of a real ubiquitous society, as Weiser (1995) predicted that technology would become so ubiquitous that society takes new technology for granted as being inseparable from everyday life.

The ubiquitous gadgets and their corresponding services will have a transformational impact on society as a whole and the lifestyle pattern of its citizens (Agarwal and Lucas 2005). Among these gadgets, smart phones are now bringing an outpouring of diverse services toward the Metaverse. Metaverse is a combination of the "meta" (beyond) and "universe" and is a three-dimensional virtual space that uses the metaphor of the real world (www.wikipedia.org). It is a combination of virtual worlds, augmented reality, and the internet. Thus, Metaverse consists of four major dimensions: Augmented reality, Life logging, Mirror world, and Virtual world, which are established on the criteria of: *Augmentation* versus *Simulation* and *External* versus *Intimate* (www.metaverseroadmap.org/overview).

iPhone is perhaps the most popular and well-publicized device made by Apple Inc. According to a Gartner report in 2009, 2.5 billion applications were downloaded, and 99.4% of the downloads were from the iPhone's application store. Given that Metaverse services are mainly enabled with these diverse applications, it seems that iPhone is the most promising candidate for the world of Metaverse.

Several of such applications were originally web-based services on PC. However, smart phones take these applications outdoors and augment them through the location-based (GPS) and individual-based (compared to PCs, phones are truly personal, belong to one individual) that only smart phones provide. Thus, Twitter, Google, iPhone, and Secondlife (T.G.I.S) was coined as an expression of this technological enjoyment in the new era. Based on the definition and the above discussion, we can say that T.G.I.S parallels the Metaverse concept.

In this article, we observe Metaverse services to analyze and compare the users' adoption patterns among these services. To draw implications about innovation and imitation effects, we utilize Bass' theory. This article is organized as follows: Sect.

2 presents a review of relevant literature; Sect. 3 explains the research model used and develops the hypotheses; Sect. 4 provides the research methodology for data collection and analysis, and the results; Sect. 5 discusses the findings of the study; and Sect. 6 concludes with the study's implications.

2 Literature review

In reviewing relevant literature, we first examine previous research on the dimensions of Metaverse and the criteria for the classification; second, the characteristics and the role of smart devices in social interactions; and finally, measurement of S-shaped technology adoption.

2.1 Types of Metaverse

Being an unprecedented concept, the definition and classification of Metaverse remains little explored in academic fields. Metaverseroadmap took the first step in defining Metaverse in 2007 and set the academic background by classifying Metaverse into Augmented reality, Life logging, Mirror worlds, and Virtual worlds (Table 1).

The criteria for this typology are based on the level of *Augmentation* versus *Simulation*, and the level of *External* versus *Intimate* (Fig. 1). *Augmentation* refers to technologies that add new capabilities to existing real systems. These technologies superimpose a calque of information layers over the physical environment so that people can have control of it. *Simulation* refers to technologies that model realities into virtualities. This process simulates the physical world as the locus for interaction. *Intimate* technologies focus inwardly, on the identity and

Table 1 Dimensions of Metaverse

Dimensions of Metaverse	Explanation	Characteristic
Augmented reality	Technologies enhance information about the external physical world. This information is layered and networked so that individuals can exploit it	External/ Augmentation
Life logging	Augmentation technologies record and report the intimate states and life histories of objects and users. They are largely divided into two kinds: Object Lifelogs, which record the environment and condition of the physical world, and User Lifelogs, which record users' lives	Intimate/ Augmentation
Mirror world	Mirror worlds are informationally-enhanced virtual models or "reflections" of the physical world. This world codes external sources such as environmental and geospatial information into the web	External/ Simulation
Virtual world	In contrast to the existing virtual worlds, the newly-emerging virtual worlds gradually simulate the economic and social life of physical world communities. The extreme simulation opens up the possibility that individuals can have a second identity in a virtual world	Intimate/ Simulation

Adapted from Metaverseroadmap.org

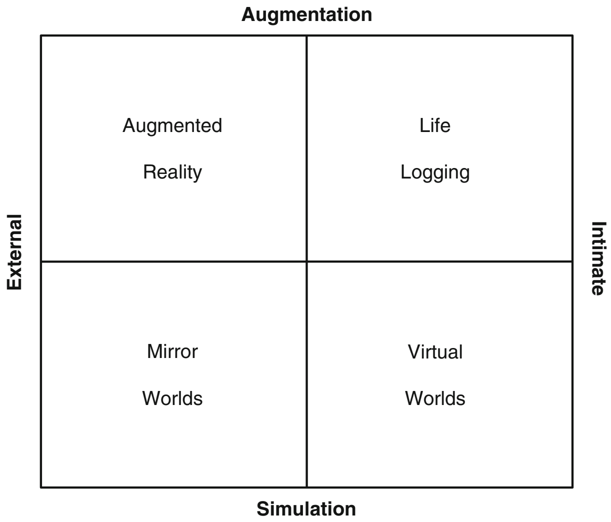

Fig. 1 Classification of Metaverse (www.metaverseroadmap.org)

actions of the individual or object, while *External* technologies focus outwardly, toward the world at large (www.Metaverseroadmap.org/overview).

2.2 Smart devices as the mean for the rise of Metaverse services

Implementation of the Metaverse world is enabled by technological support. Perhaps one of the most influential changes for Metaverse during the last few years has been the massive distribution of smart devices. Smart devices encompass smart phones, PDAs, handheld consumer devices with Internet access, and the accompanying suites of accessible services (Bergman 2000). As described by Hong and Tam (2006), the characteristics of these smart devices as multipurpose information appliances are that they have a one-to-one binding with the user, offer ubiquitous services and access, and provide a suite of utilitarian and hedonic functions. Also Lyytinen and Yoo (2002) note that smart handheld devices can successfully deliver nomadic computing.

Among those smart devices, the most recent and popular type is the smart phone. The global smart phones market grew 90% in the third quarter of 2010 alone, with vendors shipping 81 million smart phones, which accounted for 20% of all mobile phones (Kirk 2010). The smart phone is almost always available, making it an ideal system for pervasive and supportive social computing (Beale 2005).

Consumers' decision-making process on adopting a new product involves not only the mass media but also individual factors like word-of-mouth, personal preferences, and experience (Mahajan et al. 1990). Interpersonal communications constitute an important medium especially for social groups that are hardly reachable by mass media advertising (De Valck and Van Bruggen 2009; Kiss and Bichler 2008). Therefore, social interaction and imitation effects can cause an abrupt rise in technology adoption. Bass' imitation model of technology adoption (Fig. 2) shows

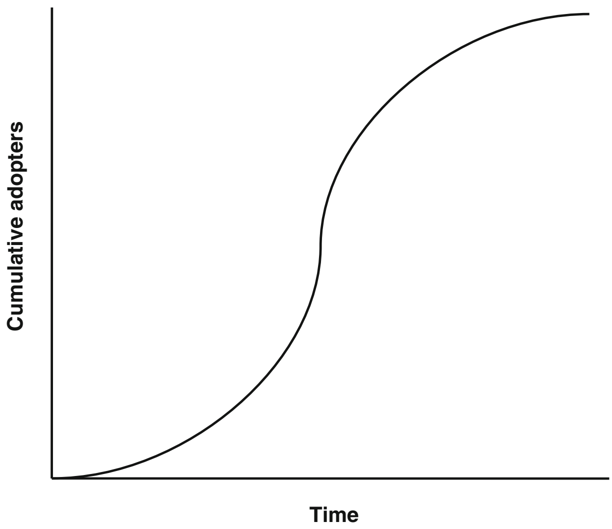

Fig. 2 The Bass/Mansfield imitation models

that during the imitation period the adoption rate rises exponentially (the concave section). Bass explained the imitation effect with the word-of-mouth: people are influenced by their peers' behaviors of technology adoption.

2.3 Technology adoption measure

While smart phones trigger more social interaction which results in an abrupt growth of Metaverse services along the service adoption curve, it would be of interest to find out how to measure such change so that one can draw implications. The adoption of IT services has a long history and has been one of the most popular topics in the information systems field (Davis 1989; Taylor and Todd 1995). However, traditional research on IT adoption is not fully applicable to modern multi-purpose appliances. Several other relevant factors have been identified in IT products diffusion, and the old models have been criticized because of their inability to account for the modern complex and networked technologies (Lyytinen and Damsgaard 2001).

The evolution of Internet-based peer-to-peer services and avalanche-like diffusion of them demonstrate the difficulties of using traditional models to predict the adoption of such services (Kivimaki and Fomin 2001). As the diffusion of multiple-purpose devices is closely related and highly sensitive to users' communities in Metaverse, peer influence effects are expected to be found. Thus, adoption will be reflected in an interrupted time series data which is difficult to explain. Rogers (1995) argues that when firms that have adopted an innovation contact the non-adopting firms, their evident superior performance will encourage non-adopters to adopt the innovation, and this results in the rapid growth stage, in an S-shaped diffusion curve. Another popular innovation diffusion models is in the marketing field: the Bass model. This model assumes that the adopters of an innovation comprise two groups. One group is influenced only by mass-media communication (external influence) and the other group is only influenced by the word-of-mouth communication (internal influence). Bass termed the first group "Innovators" and the second group "Imitators" (Bass 1969).

Innovation diffusion models have been traditionally used in the context of sales forecasting (Mahajan et al. 1990) which is only one of the objectives of diffusion models (Kalish and Lilien 1986). In addition to forecasting, many researchers have used these models for descriptive inferences. For example, Olshavsky (1980) employed the Bass model to explain that product life cycles (PLCs) of consumer durable goods are shortening because of rapid technological development, and Kobrin (1985) used it to establish that the pattern of oil production nationalization is a social interaction phenomenon. Takada and Jain (1991) exploited this model to reveal the different patterns of diffusion according to national cultures. We also chose Bass model in this study, as our purpose is to measure the Metaverse service adoption pattern influenced by innovation and imitation effects.

3 Research model

For this study, we use Metaverseroadmap's typology to group T.G.I.S: Twitter as Life logging, Secondlife as Virtual World, and Googlemap as Mirror World. We did not considered Facebook here since its characteristics overlap that of Twitter. We do not conduct analysis for Augmented reality as it represents a challenge for collecting the data. In contrast to Life logging, Mirror world, and Virtual world, Augmented reality services are mostly based on mobile applications rather than web-based (we use IP traffic as a measurement unit). Finally, iPhone sales data are measured in unit sold (Table 2).

3.1 Hypotheses development

Rogers (1995) theorized about the diffusion of innovation in terms of timing. He suggests IT adoption is influenced by a process of communication and social influence, and this forms an S-shaped curve as shown in Fig. 3. The sequential process in the adoption curve is: Innovators, Opinion leaders, Early majority, Late

Table 2 Metaverse T.G.I.S classification

T.G.I.S	Metaverse	What we employ	
		IP traffic	Sales data
Twitter	Life logging	Twitter.com	
Google	Mirror world	Maps.google.com	
	Virtual world	Secondlife.com	
iPhone			iPhone 1G, 2G, 3G, 3GS

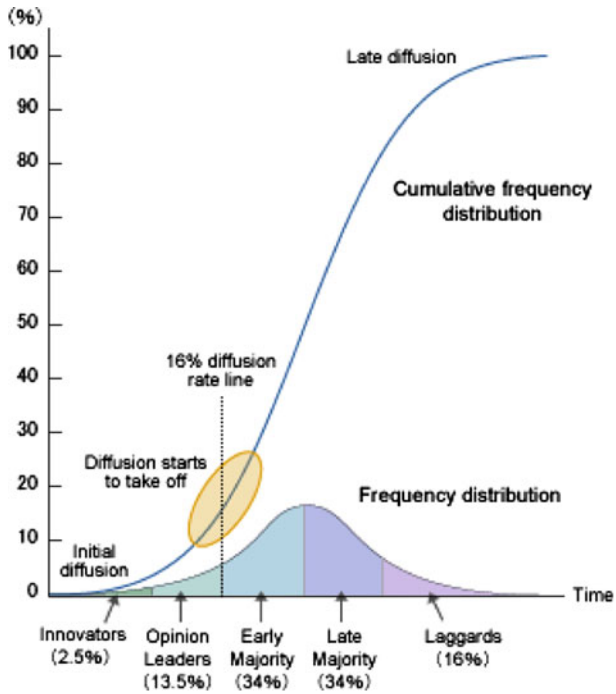

Fig. 3 Category of adopters in sequence and S-shaped curve (Rogers 1995)

majority, and Laggards. Rogers pinpointed that the major and abrupt increase along the S-shaped curve is generated among the Early majority and the Late majority and is explained by overcoming the chasm that exists between the Opinion leaders and the Early majority. A chasm is the transition phase where sufficient momentum is needed to create the de facto standard (Moore 1991).

In order to create imitation effects within groups, a social interaction is needed so the product or service could overcome the chasm. Many Metaverse services were pioneered as starts-up a few years ago as wired web-based services. With the introduction of iPhone and its current massive diffusion in the number of users and services in the last 2 years, Metaverse services offered and used have increased and are getting into the stage of mass growth. People are interacting more and influencing each other for products and services they use. Therefore, we can assume that the Metaverse services have already passed the chasm and are causing imitation effects among the groups of services. Thus, the following hypothesis is drawn:

H1 In the adoption process of Twitter, Googlemap, and Secondlife, imitation effects is greater than innovation effects.

As a social network-based service, Twitter has spreads into market through human networks. Within the service, users leave their opinions for other users to read them casually. Readers selectively enroll opinion uploaders as those with whom they have a close-knit relationship or those who are their favorite celebrities.

Thus, Twitter is an in-born social network service that strongly follows the imitation diffusion pattern.

Googlemap also relies heavily on the imitation diffusion pattern. As the number users on a certain network increases, so does the utility for that service. Googlemap originally started a merely web service, but now many other applications that exploit Googlemap have emerged as the number of users has dramatically increased over years.

Unlike Twitter and Googlemap, first time users of Secondlife need to learn much more about the new virtual world, need to be more innovative. However, once users learn and are involved in using the service, their imitation effect becomes stronger. Thus, one can induce that Twitter and Googlemap's strong network effects surpass their innovation effects (Lee and Lim 2009; Lee et al. 2010), thus have a lower innovation effect than Secondlife. Therefore, the following hypothesis is proposed:

H2 The innovation effects for Twitter and Googlemap is smaller than that for Secondlife.

Schumpeter deemed technological progress as a process of "creative destruction" in which existing products are superseded by innovations of new ones (1942). In the same mode, Hague (2002) presented the PLC point of view whereby improved products lead to rejuvenation of PLC as shown in Fig. 4.

We have witnessed such abrupt technology development in the market place during the last two decades where the greater the innovativeness of the technology, the shorter the time taken for diffusion. Figure 5 provides an insight into the speed with which new technologies have taken over the older ones. Many competitors are entering the information and communication technology (ICT) market and businesses, continuously introducing new products and services to seize a greater market share.

In contrast to tangible ICT products, innovative services have more staying-power from inertia. For example, the service of Googlemap has continued while the devices that support it have been constantly replaced over time. Unlike tangible goods, services are almost exclusively based upon person-to-person interaction (Gremler and Brown 1996). These interpersonal relationships are important for the development of loyalty to services (Berry 1995) and it takes time to build them thus,

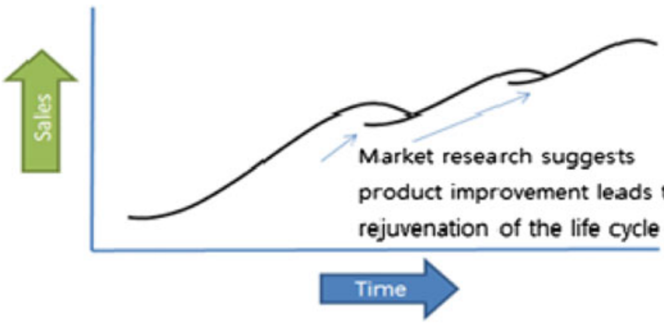

Fig. 4 Rejuvenation of the PLC (Hague 2002)

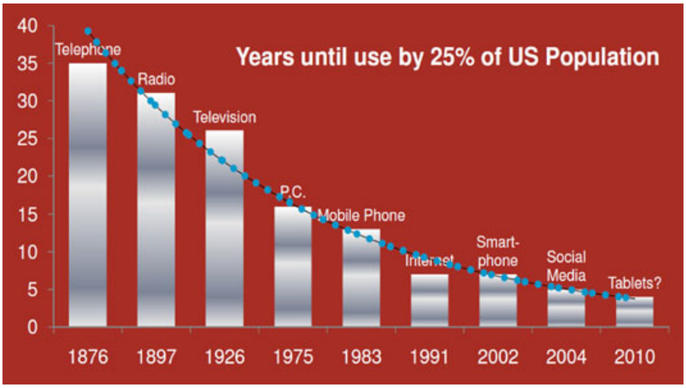

Fig. 5 Years taken until 25% of US population used the technology (Simon 2010)

making the life span of innovative services longer than that of ICT products. Considering that the iPhone is an ICT product, and Twitter, Googlemap and Secondlife are services, we propose the following hypothesis:

H3 The innovation effect on sales (adoption) is greater for iPhones than for Twitter, Googlemap, or Secondlife.

4 Research methodology

4.1 Bass model

Mahajan and Muller (1990) developed a white-noise model as a null hypothesis. They argued that the difference in the number of adopters at times t and $(t - 1)$ is random, implying that the rate of diffusion is driven by the error term as follows:

$$x(t) = x(t - 1) + e(t)$$

The nonlinear least squares method was used in this study because a linear method has some limitations like the multicollinearity and nonavailability of standard errors for crucial parameters: p (coefficient of external influence), q (coefficient of internal influence), and m (number of eventual adopters).

We adopt the Bass model against the null hypothesis to explain the diffusion due to imitation and innovation effects. Bass shows that based on the timing of the technology life cycle, the diffusion of technology will show a different shaped curve (Fig. 6).

Imitation effects are presented as exponential growth in the graph. Unlike the innovation effects curve where the speed of adoption becomes slower at the end, imitation effects bring about more adoption by communication among group members which results in exponential spread of the technology.

Bass theory implies product adoption by individuals is due to both internal (word-of-mouth) and external influences (mass communication). Word-of-mouth,

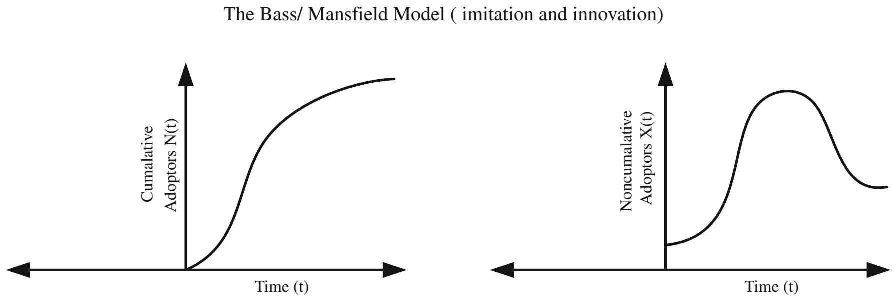

Fig. 6 The Bass/Mansfield model (imitation and innovation)

which largely encompasses the concepts of social norms, the bandwagon effect, social interaction and so on, leads to imitation effects. It is within-group influences that lead to the imitating of what others do. In contrast, adoption by external influences refers to product's or service's innovation. Users' perceptions solely of the product are considered but have nothing to do with those of other users. Bass incorporates these two factors, developing the following equation as a mixed model.

$$\frac{\mathrm{d}N(t)}{\mathrm{d}t} = [p + qN(t)] + [m - N(t)]$$

where $N(t)$ is the number of cumulative adopters, p is the coefficient of external influence (imitation), q is the coefficient of internal influence (innovation), and m is the market potential or potential number of ultimate adopters (Venkatraman et al. 1994).

4.2 Data selection

There has been a significant amount of research on the adoption of technologies, which did not precisely measure the actual usage. When one measures web-based service adoption, measurement by the number of registered users is not valid because registration does not guarantee actual use. Recently, there are many internet service companies that provide data gathered from IP traffic. These data are often used in the marketing field. Among them, Unique Visitor and Visits are the most popular indicators for website usage. We collected two-year time series data from one of these traffic information companies, the Compete.com.

Wollebaek and Selle (2002) separate the notion of scope and intensity. Scope is a concept that represents the size of the membership while intensity indicates the participation of members. Intensity is measured by the amount of time the members spend in a certain session. Thus, we borrow the concept of intensity to reflect the actual usage of the services. In this study, we use Visit counts, an IP traffic indicator. Unlike Unique Visitor, which reflects only IP traffic information logged onto a site (and thus is counted as one hit regardless of the length of the stay), data of Visits are initiated when a user logs onto a site. As the user stays on the site, the Visit is live. Visits are counted during the stay for every 30 min interval.

4.2.1 Twitter.com for Life logging

The example of Life logging focuses on capturing life records. These records might be letters, photos, music, movies, or daily activities. In an interview, Gordon Bell, a researcher at Microsoft explains that the use of Twitter.com proves that people instinctively capture more life records whenever there is an easier way (Elgan 2009). Metaverseroadmap defines Life logging by two characteristics: Object lifelogs and Users lifelogs. Twitter represents Users lifelogs, since users can log their intimate details via Twitter in real time.

4.2.2 Maps.google.com for Mirror world

In 2006, Google first introduced "Google Maps for Mobile" for any Java-based phone or mobile device. This was a basic form of utilizing web-based service on mobile phones. Subsequently, in November 2007, "Google Maps for Mobile 2.0" was released. It introduced a more advanced function of tracking users' location, and this service became available and flourished on several mobile platforms including the iPhone in December 2008. Any device that has wireless communication capability can connect to the website and get the geographical information. In contrast to iPhone 2G, iPhone 3G is equipped with GPS. This allows users to have more personalized location services. The service areas are diverse. People can exploit the GPS function for navigation, real life social networking, or location tracking games.

4.2.3 Secondlife.com for Virtual world

In this study, Secondlife.com is used as a representative example. Although there are several other virtual worlds, such as online games and social networking sites, only Secondlife.com fits the characteristic of Metaverse. Secondlife is the Internet's largest user-created 3D virtual world community. Kumar and Chhugani note that Secondlife presents a single persistent world where users can transparently roam around without predefined objectives and it is the most popular Metaverse (2008). Gartner predicted 80% of active internet users would have a Secondlife account in the virtual world by the end of 2011 (2007).

To support Secondlife service availability on mobile phones, various efforts have been undertaken. For example, there are applications such as VolleeX, and Sparkle IM. VolleeX acts as a bridge between a mobile phone and a Vollee server running a PC game or application. Sparkle IM is especially oriented to the iPhone, connecting the virtual world with its users.

4.3 Coding process

We coded the Bass formula into SAS software with the gradient method. The purpose of using the gradient method is because of its function of fixing the number of potential adopters of iPhones during a specified period of time, 2 years in this study. As the mass distribution of iPhones took place during the fourth quarter of

2008, we collected data that spans the period from December 2007 to December 2009.

In terms of data purification, large numbers of IP traffic values were divided into reasonably sized sets for convenience. Also since we needed at least ten units of time series data, and more data is better than less, we used per-month data rather than per-quarter data. For the analysis of each service, the tests were conducted several times applying different parameters for p, q, and m, to make sure that the result would not be seriously biased by them.

4.4 Results

In our proposed model, a fixed number of adopters is expected to reach at the end point by design. Thus, we could draw two curves: the actual measurement and the theoretical one for a comparison.

Twitters' visit counts revealed a significant model fit, as shown in Fig. 7. Another major finding was that imitation effects were larger than innovation effects. The graph clearly indicates adoption was boosted right after the fourth quarter of 2008.

Users' Visit counts on Google maps also highly exceeded Bass's expectations, as shown in Fig. 8. In addition, there was a big increase around the fourth quarter of 2008, the time of the iPhone 3G release. The growth of Google maps' visitors more closely follows the model fit. Although the coefficients, the innovation factor, p and the imitation factor, q were about the same as those of Life logging, Mirror world had a higher significant F value than Life logging.

The results for Virtual world shows that the model fit and null value were not significant, as shown in Fig. 9. Even though the graph visually shows us that the use of Secondlife.com surged when the iPhone's use spread massively in the market during the fourth quarter of 2008, this model does not appear to reject the null hypothesis. This is mainly because of the indented shape of the actual use graph. Although an explicit increase in the number of adoptions was shown, this did not yield constant usage.

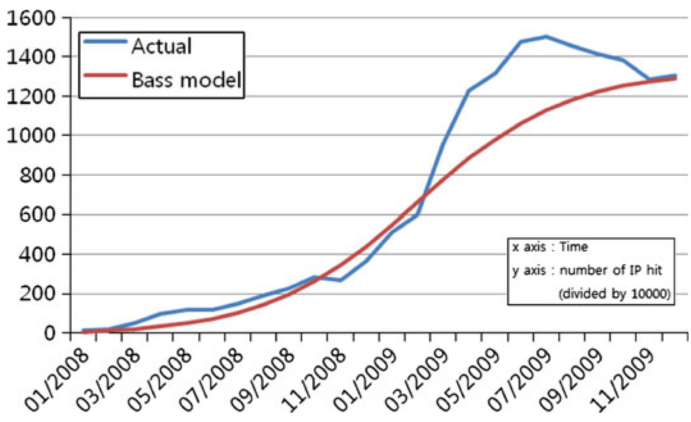

Fig. 7 Twitter.com

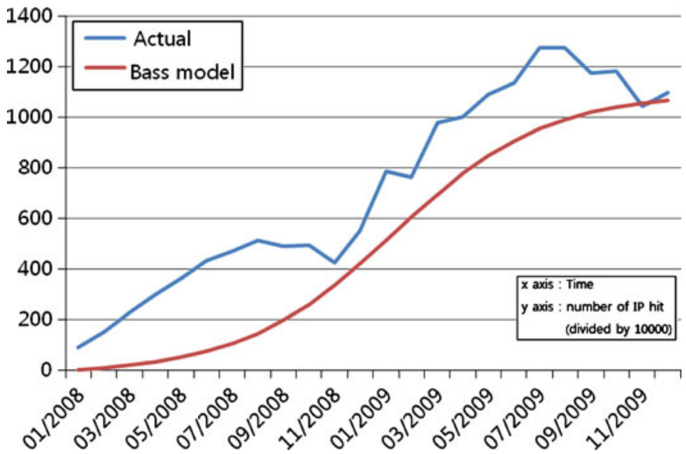

Fig. 8 Maps.google.com

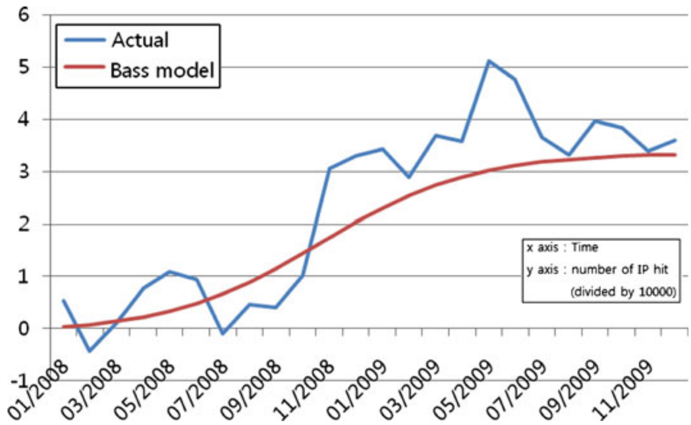

Fig. 9 Secondlife.com

Interestingly, the iPhone sales curve appears to perfectly fit the Bass model, as seen in Fig. 10. iPhone sales encompass data for iPhone 1G, iPhone 2G, iPhone 3G, and iPhone 3GS. This indicates the product has evolved fast enough for users to replace the old version with a new one which accelerated the sales. Good model fit makes it easier to predict its life cycle as to when the iPhone will mature and how big the market size will be.

We conducted an extra analysis for iPhone sales. It is worth forecasting the future sales of iPhones, as smart phones have been demonstrated a powerful support for Metaverse service diffusion. We answer this by measuring expected sales of the iPhone in the future, as shown in Fig. 11.

Table 3 summarizes the results of our analysis. There are several important points that deserve our attention.

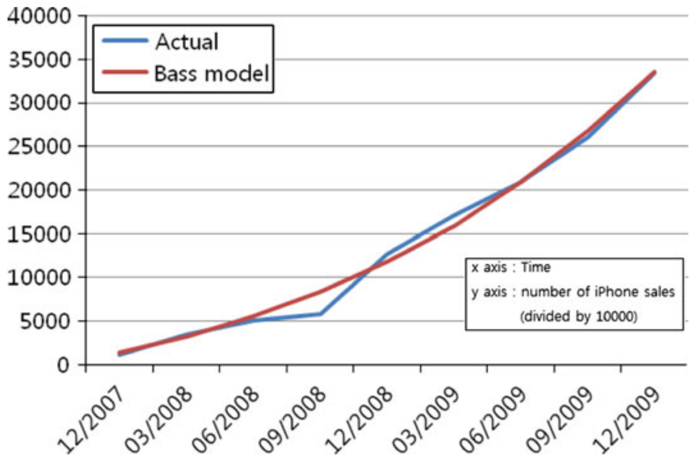

Fig. 10 iPhone sales

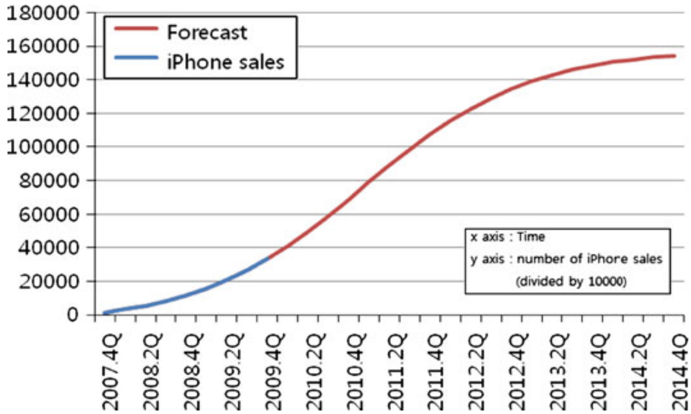

Fig. 11 Forecast of iPhone sales

First, the results tell us that the q levels for all dimensions are much greater than the p levels. This means imitation effects are much greater than innovation effects, supporting our H1. Second, the p level for Virtual world is about two or three times higher than that of Life logging and Mirror world although it did not have a significant F and t value. However, this does not imply that the Virtual world results are meaningless. This is because we employed IP traffic information to measure usage intensity, and the weak t value is due to the occasional minus diffusions that could often happen among IP logs. As Bass' experiment was based on products, not on services, he did not consider recessions as normal phenomena and defined them as a white noise model. Thus, considering the experiment condition, although the F and t values were not significant, we judge the high p value for Virtual world to be meaningful. Third, iPhone sales as an ICT product showed greater innovation effects than Metaverse services. For ICT products the time period of their

Table 3 Test results

	Twitter	Googlemap	Secondlife	iPhone sales
Parameter estimation				
p (innovation effect)	0.00276	0.00377	0.00833	0.00821
q (imitation effect)	0.3383	0.3331	0.3393	0.2361
Model fit				
F value	7.48***	2.63*	0.73 (not sig.)	15.96***
R^2	0.52	0.27	0.075	0.8886
Hypothesis testing				
Null value	$\alpha = 0$	$\alpha = 0$	$\alpha = 0$	$\alpha = 0$
Test statistic	$t = 2.54$**	$t = 1.32$ (not sig.)	$t = 1.55$ (not sig.)	$t = 2.65$**

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

replacement by the new products is faster than services. When replaced, the product starts to exhibit some new innovation effect again and again.

5 Discussion

We have found that Twitter, Googlemap, Secondlife, and iPhone, all show greater imitation effects than innovation effects. From this result, we assume that Metaverse services are now in the maturing stage in service adoption. Although we gained a weak t value for Secondlife, we believe this comes from the characteristic of Virtual world that it *simulates* reality into virtuality. This requires high-end devices perform the task. Since the iPhone's hardware and applications cannot support the simulation fully as yet, it may result in user resistance. Also, unlike Googlemap, a mirror world where services are more external world-oriented, Virtual world users may not find it beneficial to use intimate services on mobile devices. Thus, the effects of intermittent recessions were found on the graph for these reasons, and subsequently, an insignificant q coefficient occurred.

We also found an interesting result for Googlemap. We can borrow the concept of network externality to explain the result. Network externality means that the utility that a given user derives from a good depends on the number of other users who are in the same "network" (Katz and Shapiro 1985). This concept has been further developed to explain the reason for imitation effects in regard to the product usage. Katz and Shapiro (1985) explain network externalities in the manner of competition and compatibility. In other words, the wider the scope of the technology, the more inter-business competition and thus technology compatibility comes into play. As Googlemap shows significant imitation effects, we can predict that there will follow more related services and technology infrastructures.

We believe Twitter's imitation effects will be derived from users' social interaction within the service, because unlike a mirror world, Twitter, which is Life logging focuses heavily on individuals' information. Resnick (2002) suggests social interaction, mediated by technology may produce “SocioTechnical Capital”. This socio technical capital is upgraded with the help of technology. Girgensohn and Lee (2002) also argue that such capital causes future social interactions through web-based technology. As community networks become stronger than ever in support of smart devices, and since people continuously leave trails of their lives on the web, this behavior can be intensified with the help of smart devices in the years to come.

Technologies that are in the business of connecting people to people are now in high demand. Thus we conclude the imitation effects shown in Twitter are more based on the human community, rather than the scope of technology usage. Metaverse grows as technology is opening up the possibility of seamless and ubiquitous computing. As we noticed in relatively high innovation effects for the iPhone with a perfect *F* value, it is a relatively new product for customers compared to other Metaverse services. Perhaps this is because the iPhone is a tangible product with the flexibility for diverse purposes, and thus the users are more sensitive to its innovative aspects than their former devices. We believe this is the main reason that the evolution of iPhones 1G, 2G, 3G, and 3GS has been so fast. Thus, we conclude that now the timing is right for enterprises to focus on ICT products that support Metaverse services more intensively because they can survive only through constant investment in innovation.

6 Conclusion

Research on Metaverse is still at an early stage, and most Metaverse research is now being conducted at the conceptual level as compared to other diversified methods in IS studies. This research analyzed the four dimensions of Metaverse with different characteristics in the hope that it will help pave the way for technology diffusion analysis in the field. From the industrial point of view, this research can shed new insights to Metaverse service entrepreneurs about future directions for the industry. They can exploit the implications of how technological *Augmentation* and *External* affect social interaction, thus leading to S-shaped growth in the years to come. Because there are not many generalized theories about Metaverse due to its short history, the efforts to research the service adoption based on the Bass model will provide a new resource for decision-makers in the relevant industries.

Although measuring the intensity of Metaverse service usage represents a new ground, continuous research of Metaverse and its relationship with smart devices requires many improvements in analysis.

First, since this research used the Bass model to reveal the intensity of the usage, the experiment conditions are a bit different from those of the original Bass study. Bass employs an enterprise system while we used IP traffic. Using IP traffic has pros and cons. For pros, we can mirror the usage more accurately, and for cons, the information is volatile in that it contains occasional falls and causes a weak *t* value. Thus, to have stronger experimental support, it would be better to use cumulative data and at the same time incorporate data that mirror the intensity of usage in further research. Second, it would be better to include other variables that affect the Metaverse distribution. There are other variables than just innovation and imitation effects, such as changes in users' preference and cultural values, the launch of new business services, or changes in government policies. Therefore, a comprehensive approach incorporating business, cultural, political, psychological, and sociological factors should be used in the future.

Acknowledgments This work was supported by the Korea Research Foundation Grant funded by the Korean Government (KRF-2009-32A-B00055) and completed with Ajou university research fellowship of 2009–2010.

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