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A bibliometric method for measuring the degree of technological innovation

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ABSTRACT

Knowing the degree and stage of a product's innovation is essential for technological forecasting and beneficial for governments and firms that want to come up with product promotion strategies and prioritize investments. Bibliometric analysis has been widely used as a practical tool to evaluate scientific activities. Although there were many bibliometric-based attempts to model product innovation stages, there have not been any trials that approach it from the standpoint of uncertainty reduction in technological product innovation. This paper suggests two hypotheses: 1) at a macro level, the year-to-year difference in relative research volumes of each component decreases over time as the uncertainty of a product decreases; and 2) at a micro level, the year-to-year difference in relative research volumes of each component is correlated with the technological life cycle of a product's core component. In addition, we provide empirical evidence that supports the hypotheses in the case study of mobile phones. From the evidence, we conclude that bibliometric analysis using research papers can measure the uncertainty in a product's technological innovation.

1. Introduction

Knowing the degree and stage of a product's innovation is essential to technological forecasting (Watts and Porter, 1997) and beneficial for governments and firms that want to come up with product promotion strategies and prioritize investments (Abernathy and Utterback, 1978; Cusumano et al., 2007). It is because that the stimuli and barriers to success are different in each stage of product innovation. For example, cost reduction is not a good policy at the early stage of product innovation. Also, the government's policy to force a young industry to be standardized before a dominant design (also known as an industry standard) emerges, has been proven to fail (Abernathy and Utterback, 1978). Despite its importance, the difficulty of measuring the degree of product innovation has hindered the progress and practical use of the product life cycle model.

Bibliometric analysis has been used as a practical tool to monitor technology (Coates et al., 2001) and evaluate scientific activities. When bibliometrics focuses on measuring the quality of science and technology, it is often called scientometrics (Hood and Wilson, 2001). To date, many trials based on bibliometric methodologies have been done to measure the degree of innovation in terms of technology, product, or industry (Watts and Porter, 1997); however, bibliometric analysis suffers from the following limitations: 1) the number of published scientific papers is not indicative of the quality of research activity; 2) much scientific development is not published (Watts and Porter, 1997); and 3) most scientific publications are not product-based.[1] Although bibliometric analysis may be less accurate than other traditional analysis methods due to these limitations, bibliometric analysis still has its own merits. It is fast, low-cost, and can complement existing methods. At the least,

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[1] R&D that produces scientific papers is oriented to science and technology. Products or product components are all necessary items for technology-related activities (Guglielmi et al., 2010) and are associated with different types of technologies. Thus, in bibliometric analysis, if a scientific paper about a technology is related to a product with a clear statement, the paper is considered to be related to the product.

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bibliometric analysis can be used as a preliminary hypothesis-screening tool before launching a major analysis project.

The analysis based on the S-curve pattern of product life cycle (e.g., Meyer et al., 1999; Bengisu and Nekhili, 2006; Daim et al., 2006; Liu and Wang, 2010; Ryu and Byeon, 2011) is a good example that uses a growth pattern of the number of related papers. However, in bibliometrics analysis, there has not yet been a trial that approaches it from the standpoint of uncertainty reduction in technological innovation. The uncertainty may be technological, market-related, and regulatory/institutional (Jalonen, 2012; Jalonen and Lehtonen, 2011). In this paper, we show that bibliometrics can be used to measure the degree of technological innovation in the Abernathy and Utterback model (Abernathy and Utterback, 1978; Utterback and Abernathy, 1975; Utterback, 1994). To this end, we suggest two hypotheses: 1) at a macro level, the year-to-year difference in relative research volumes of each component decreases over time as the uncertainty of a product decreases; and 2) at a micro level, the year-to-year difference in relative research volumes of each component is correlated with the technological life cycle of a product's core component. We provide empirical evidence to support these hypotheses from the case study of mobile phones. Mobile phones were chosen as the subject of the case study because their empirical results can be validated easily, and their evolution of technology is well studied (e.g., Dalum et al., 2005; Koski and Kretschmer, 2007; Lin et al., 2009; Ansari and Garud, 2009; Giachetti and Marchi, 2010; Chen et al., 2012; Kim, 2012).

This study was motivated by the work of Frenken and Leydesdorff (2000) who conducted a time series investigation about the amount of changes in scaling patterns among 143 designs in civil aircraft (1923–1997) to justify a heuristic. The heuristic is that many incremental improvements are associated with the rescaling of designs within the range of existing standard designs, whereas the major innovation that brings out a dominant design – a design that achieves a dominant position as a market or technological standard – is accomplished based on the redesign of existing standard forms and structures (Sahal, 1985). This redesign radically changes ratios between the characteristics of a product (e.g., increasing/decreasing the ratio of front and back wing lengths). Their work, whether they intended it or not, also showed the possibility that methodologies from information theory can be used to measure the extent of dominance, diffusion, and convergence of product designs.

The subsequent sections of the paper are organized as follows. Section 2 presents the theoretical background about a technological innovation process and the uncertainty existing in it. Section 3 reviews the work of Frenken and Leydesdorff (2000) in detail, and Section 4 suggests our model that measures a product's degree of development using the product life cycle viewpoint. Section 5 presents the case study about mobile phones, which validates our model, and Section 6 concludes the paper with discussion.

2. Background

2.1. Process of technological innovation

Technological innovation is the successful adoption of a technology-based invention for products and processes. The level of success of the adoption is determined by the economic value created in the marketplace (OECD, Oslo Manual, 2005). A mere adoption of an invention is not technological innovation until the effect of innovation is diffused in the marketplace and produces economic benefits for a firm that wants innovation. For technological innovation, a product or a process should be new or significantly improved for the marketplace, industry, or at least for the firm. In the perspective of product innovation, a technologically new product can be born by adopting new technology or devising new uses of existing technology, while a technologically improved product can be created through the use of higher-performing components or materials, or the innovation of a sub-system of the product (OECD, Oslo Manual, 2005).

There are different kinds of perspectives on what type of typology to use to classify technological innovations (Garcia and Calantone, 2002). Based on the general perspective, technological innovations are categorized into two classes: radical and incremental. Radical innovation, which creates a technologically new product, involves greatly "competence-destroying" technological advancements. Incremental innovation, which is related to a technologically improved product, involves modestly "competence-enhancing" technological changes.

The process and characteristics of technological innovation can be described as models such as those by Utterback and Abernathy (1975) and Roberts and Frohman (1978), or the S-curve model by Roussel (1984) and Foster (1986). Based on the Abernathy and Utterback model (Abernathy and Utterback, 1978; Utterback and Abernathy, 1975; Utterback, 1994), the innovation process in an industry is summarized in three phases: *fluid*, *transitional*, and *specific*.

In the fluid phase, market needs, design criteria, and performance requirements of a product are ill-defined. The technical uncertainty is high and the changes of the production and process are frequent. Also, the process is composed of non-standardized or nonspecific operations, which leads to firms developing a variety of products without using a stabilized product concept. However, the number of firms involved in an industry is relatively small; competition between them is focused on maximizing functional performance but not on standardizing and cost-minimizing product manufacturing. In this period, firms invest in radical product innovation rather than process innovation. Firms believe that considering customer needs can help them become dominant players in the market; consequently, product innovation occurs more frequently than process innovation.

The more a firm's product develops, the more the technical uncertainty reduces; after the target becomes clear, firms invest more in the formal research and engineering of a product. Cost competition and reduction in the number of incumbent occur during the transitional phase. The emphasis of investment shifts from radical product innovation to process innovation and product differentiation which uses a firm's internal technical capabilities. As a product concept becomes stable, a dominant design is established. Due to the advent of a dominant design, the increased production volume pressures the incumbents to discuss the standardization of a product for the sake of a production economy. The selection of a dominant design is not radical innovation even though it generally takes the form of a new product. Rather, it is a result of creatively synthesizing technological innovations that independently exist in prior product variants. Interestingly, "from an evolutionary perspective, dominant designs are not driven by technical or economic superiority, but by sociopolitical/institutional processes of compromise and accommodation between communities of interest moderated by economic and technical constraints" (Tushman and Murmann, 2002, p.19).

In the specific phase, process innovation is common, but product innovation is rare. Since firms' activities are generally focused on cost efficiency, they prefer process innovation which is not disruptive and expensive. Firms focus their capacity on adopting other innovations from the outside (Abernathy and Utterback, 1978). A dominant design established in the transitional phase leads to massive investments from incumbents, which makes it difficult for small firms to enter the industry. As a result, large firms dominate the industry, which leads to the shakeout of incumbents who fall behind in investment competition (Tushman and Murmann, 2002; Utterback and Suarez, 1993). An innovation process can be restarted in every phase due to the emergence of new technology, technology discontinuity (Anderson and Tushman, 1990), or a sudden or cumulative change in the market (Utterback and Abernathy, 1975).

2.2. Uncertainty in technological innovation

The adoption and implementation of innovation can be conceptualized as the process of uncertainty reduction created both in the internal and external environments of a firm. From the systematic literature review, Jalonen (Jalonen, 2012; Jalonen and Lehtonen, 2011) identified eight factors that create uncertainty in the innovation process: technological uncertainty, market uncertainty, regulatory/institutional uncertainty, social/political uncertainty, acceptance/legitimacy uncertainty, managerial uncertainty, timing uncertainty, and consequence uncertainty. Although other factors affect the processes of technological production innovation, technological uncertainty affects it the most. Jalonen (2012, p.24) argued that "the technological uncertainty in innovation arises due to a lack of knowledge of the details of new technology or due to a lack of knowledge required to use new technology."

In general, a product consists of many components (or subsystems) in a hierarchical order. Technical innovation can also be defined as a new combination of components or a reestablishment of the relation that was previously established between components (Fleming, 2001). Once inventors obtain knowledge and performance improvement of a specific component, they begin to seek other linked components that can also be improved. This means that the innovation of one component stimulates the innovation of other related components.

Customer needs precede technologies as a stimulator of innovation in product innovation. In the first stage of product innovation, the core technological innovation based on custom needs is achieved, and the relations between components are more or less uncoordinated due to the lack of understanding of components. Approaching to the next stage, the innovation of relatively less important peripheral technology linked to the core technology follows thereafter and the relations between components begin to be coordinated. Broadening our understanding of components and accumulating more knowledge decrease the uncertainty in technological innovation from the peak at the beginning of innovation (Mueller and Tilton, 1969). The closer the innovated component is positioned to the core, the more sweeping effects it has on the innovation of peripheral components (Abernathy and Utterback, 1978; Tushman and Murmann, 2002).

The innovation can be summed up as an uncertainty reduction on a product, and the uncertainty in innovation may decrease in a pattern similar to that of the product innovation shown in the Abernathy and Utterback model.

3. Research motivation and hypotheses

This study was motivated by the work of Frenken and Leydesdorff (2000). They conducted a time series investigation about the amount of changes in scaling patterns among 143 designs in civil aircraft (1923–1997). For the features of the experiment, they used 30 ratios composed of the following six product characteristics: engine power, wing span, fuselage length, take-off weight, speed, and range (e.g., engine power / wing span, range / speed, and so on). They showed that the methodologies from information theory can be used to measure the extent of diffusion and convergence of product design. In their work, a low rate of diffusion turned up in the experiment stages of product development, and a high rate of diffusion turned up in the diffusion stages of product development, corresponding to the cyclic dynamic of scaling trajectories of civil aircraft and helicopter technologies. They justified the heuristic that incremental improvements are associated with the rescaling of component ratios within the range of existing standard designs, while major innovations brining out dominant designs are accomplished based on redesigns of existing standard forms and structures (Sahal, 1985) which cause radical changes of ratios between the characteristics of a product.

In Frenken and Leydesdorff's work (2000), two aspects about the process of technological innovation over time can also be observed: 1) at a product level, uncertainty in technological innovation decreases, and 2) at a component level, uncertainty in technological innovation repetitively increases and decreases, which corresponds to the cycle of dominant design changes.

The goal of this paper is to show that these two aspects are observed not only through direct analysis of characteristics of a product but also through bibliometric analysis of research papers. We justify this by validating the following two hypotheses.

Hypothesis 1. At a macro level, the year-to-year difference in relative research volumes of each component decreases over time as the uncertainty of a product decreases.

Hypothesis 2. At a micro level, the year-to-year difference in relative research volumes of each component is correlated with the technological life cycle of a product's core component.

We show that a bibliometric analysis of research papers can be used to measure the degree of uncertainty in a product's technological innovation, and thus bibliometric analysis can be used as a convenient tool for measuring the degree of product innovation. The logical basis for these hypotheses is as follows. The uncertainty of a product affects the specification of the product's components. Also, the relations between the components are uncoordinated at the initial stage of product innovation due to the lack of understanding of components; however, the relations become coordinated over time. Likewise, the research subjects of product's components at the initial stage of product innovation are unclear to researchers. Consequently, this uncertainty makes a relatively large year-to-year difference in the shares of each component in research volumes, and the difference decreases over time as the uncertainty of a product decreases.

4. Model

For this study, we apply Kullback–Leibler divergence (Kullback and Leibler, 1951) and critical transition methods to the number of research papers which Frenken and Leydesdorff (2000) used.

4.1. Kullback–Leibler divergence

Kullback–Leibler divergence (K–L divergence) is an entropy-based measure of the difference between two probability distributions, p and q. K–L divergence is defined in Eq. (1):

$$D_{KL}(q\|p) = \sum_{i}^{n} q_i \log_2 \frac{q_i}{p_i} \tag{1}$$

where p is a prior distribution $(p_1,\dots, p_n)$ and q is a posterior distribution $(q_1,\dots, q_n)$. Frenken and Leydesdorff (2000) used 30 ratios composed of six product characteristics as features for the experiment; therefore, the value of n is 30 in their study. In our study, we used K–L divergence to measure the year-to-year differences in the shares of volume (of published papers) associated with the components of a product. For example, if we consider the three major components of mobile phones which are battery, antenna, and memory, we have the following ratios: battery/antenna, battery/memory, and antenna/memory. Thus, n is 3, p is the distribution of the three ratios in the previous year, and q is the distribution of the three ratios in the year in question. This is explained in detail in the following section.

K–L divergence takes its value in $[0, \infty]$. If the K–L divergence value of p from q is low, it means the currents ratios changed very little compared with the previous ratios, and vice versa. For example, let p and q be the distributions of the ratios in 2000 and 2001, respectively. If the K–L divergence value is zero, the distribution in 2001 did not change since the distribution in 2000. From the product innovation viewpoint, this can be interpreted as having no innovation or being only a scaled version of the former designs. Frenken and Leydesdorff (2000) commented on the meaning of K–L divergence ("I" refers to K–L divergence):

> We shall use I as a measure of the degree of scaling between two product designs: the lower the value of I, the more similar are the ratios between two product designs and the more the latter design can be considered as a scaled version of the former designs. (p. 334)

K–L divergence is an asymmetric measure, which means the order of distributions affects its value. In the example case above, $D_{KL}(2001\|2000)$ and $D_{KL}(2000\|2001)$ may have different values and may need different interpretations. Frenken and Leydesdorff (2000) used these similar but distinct values to measure the degree of *diffusion* of present product characteristics to its subsequent products and the degree of *convergence* of present product characteristics from its precedents. Frenken and Leydesdorff (2000, p.336) argued that "a low diffusion-value [convergence-value] indicates a high degree of diffusion [convergence] of a product design, while a high I-value indicates a low degree of diffusion [convergence]." From this perspective, they argued that the period with high K–L divergence is relevant to an experimentation stage, and the period with low K–L divergence is relevant to a diffusion stage. This corresponds well to the cyclic dynamic of scaling trajectories of the technological paradigm (Frenken and Leydesdorff, 2000).

4.2. Critical transition

The transition at t is deemed critical for the evolution of a production if the relation of three K–L divergences at t − 1, t, and t + 1 fails to satisfy the triangular inequality as shown in Eq. (2) (Fig. 1). Critical transition in product development occurs when design B plays an important role which Frenken and Leydesdorff (2000) described as boosting the signal from design A. Critical transitions are associated with the emergence of innovative designs.

$$D_{KL}(B\|A) + D_{KL}(C\|B) - D_{KL}(C\|A) < 0 \tag{2}$$

In the subsequent section, the suggested hypotheses are tested with K–L divergences and critical transitions for mobile phone technology, and compared with the known history of mobile phone technology. The readers who want more information about K–L divergences and critical transitions can refer to Frenken and Leydesdorff's work (2000).

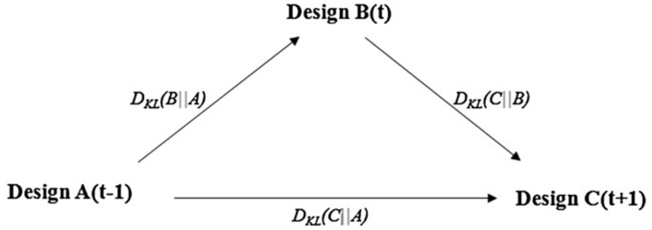

Fig. 1. Product evolution triangle for the explanation of critical transition.
(Adapted from Frenken and Leydesdorff, 2000).

Table 1
Mobile phone (mobile communication) evolution.

Generation	Time period*	Definition (Lin et al., 2009; Chen et al., 2012)	First starting year**	Stage of evolution (Giachetti and Marchi, 2010; Utterback and Suarez, 1993)
1G	1970s–1990s	Analog	AMPS in 1978 NMT in 1981	Introduction
2G	1990–2000	Digital narrow band circuit data	GSM in 1991 CDMA in 1996	Growth
2.5G	2001–2004	Packet data	GPRS in 2000 EDGE*** in 2003	Shakeout
3G	2004–2005	Digital broadband packet data	UMTS forum in 1996 UMTS specification in 1999 CDMA2000 specification in 1999 UMTS pre-commercial service in 2001 UMTS in 2003 CDMA2000 in 2000	Shakeout
3.5G	2006–2010	Packet data	HSDPA in 2006	Maturity
4G	2010–	Digital broadband packet All IP Very high throughput	LTE project for specification in 2004 LTE specification release in 2008 LTE in 2009 First large-scale LTE in 2010 LTE Advanced specification in 2011	Maturity

Referenced from:
* 1 g vs 2 g vs 3 g vs 4 g vs 5 g comparison differences and analysis. http://www.teqlog.com/1g-vs-2g-vs-3g-vs-4g-vs-5g-comparison-differences-and-analysis.html.
** History of mobile phones. http://en.wikipedia.org/wiki/History_of_mobile_phones.
*** EDGE is sometimes called 2.75G.

5. Case study

To validate the hypotheses, we conducted a case study about mobile phone technology evolution. The history of mobile phone technology evolution has been well studied by researchers, and thus it is appropriate for our case study which justifies our hypothesis. The first part of this section surveys the evolution of mobile phone technology, and the second part validates our hypothesis using diffusion, convergence, and critical transition, all of which are computed with the bibliometric approach.

5.1. Technological evolution in mobile phones

Major changes at one level affect the changes of interdependently linked products and processes, and in terms of product innovation, the changes associated with core subsystems impact the final assembled product more than the changes associated with a peripheral subsystem. This is the case especially for the electronics industry due to the strong interdependency between components and circuits (Abernathy and Utterback, 1978). The evolution of mobile phones can be traced back to the successive generations of mobile communication technologies. Ever since the concept of mobile telephony was first presented by AT&T Bell Labs in the early 1970s, mobile phone technology has continued to evolve with each generation through technological advances during the last four decades. The current mobile phone technology is called 4G technology. 5G technology is yet to be defined and may be seen in the 2020s. The history of mobile phone technology is summarized in brief (Table 1 and Fig. 2).

5.2. 1G (1970s–1980s)

The 1G mobile phone system, which used an analog signal, was limited to the service of basic voice communication. Although the adoption of microprocessor and semiconductor technologies was a helpful improvement, the mobile phone was too large, heavy, and expensive; it was mainly mounted in cars or sold for business use. In addition, the communication quality was unsatisfactory due to the frequent noise and interference both of which are typical of analog signals. In this period, competitive dynamics and industry structure in mobile phones could be well explained by the Abernathy and Utterback model. Also, a consumer's major uncertainty was related to the usefulness of a new product's technology (Giachetti and Marchi, 2010).

5.3. 2G (1990–2000) and 2.5G (2001–2004)

2G technology was discriminated against 1G in the point that its technology was based on digital signal and its service was broadened to simple data services such as text message. The advent of data services made improvements in transmission speed and voice communication quality both of which have become main research subjects. However issues about fraud prevention and encryption of user data have emerged (Ashiho, 2003). Competition in the mobile phone industry began with 2G. From the production perspective, the main concern among mobile phone manufacturers was phone miniaturization, while from the technology perspective it was the competition – to be a dominant technology for the next generation of mobile communication – between GSM and CDMA. GSM was implemented based on asynchronous transfer network technology under the leadership of Europe, and CDMA was implemented based on synchronous transfer network technology under the leadership of the United States.

During the first half of the 1990s, product technologies differed widely since firms did not fully understand customer needs for product features. After mobile phones underwent a revolution which started in the mid-1990s, they became pocket-sized and a consumer good. Due to new features such as games, the number of consumers increased sharply and the

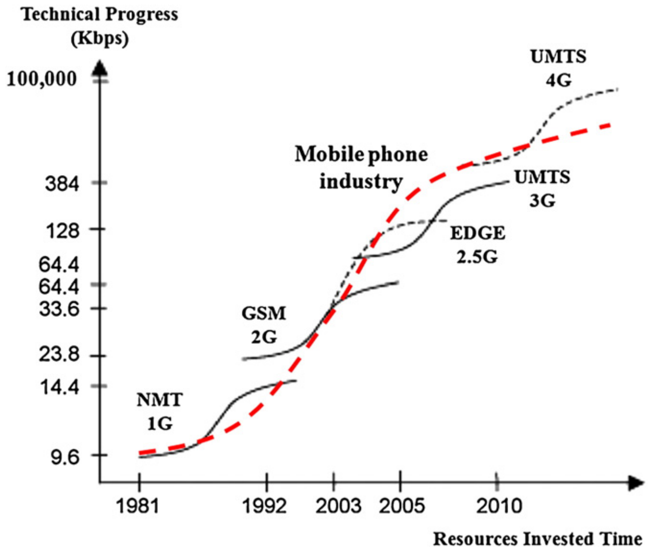

Fig. 2. Evolution of mobile phone and mobile communication technology.
(Adapted from Dalum et al., 2005; Ansari and Garud, 2009).

market attracted new participants. Firms began to invest in R&D, outsource component manufacturing, and invest in process innovation for the economies of scale (Giachetti and Marchi, 2010). Koski and Kretschmer (2007) investigated the evolution of product innovation and features such as weight, talk time, and standby time in mobile phones from 1991 to 2003. The average weight continued to decrease after 1997, and the average talk time and the average standby time continued to increase but then steadied at a certain level in 1995. In 1998, Nokia released the first cell phone without an external antenna whip or stub-antenna.[2]

Before moving from 2G to 3G, there was a transitional generation, 2.5G technology, which still used the 2G system infrastructures but implemented a packet-switched network domain as well as a circuit-switched domain (Farooq et al., 2013); 2.5G's transmission speed was comparable to that of 3G and new services were introduced..

5.4. 3G (2004–20005) and 3.5G (2006–2010)

The 2G system was unable to greatly increase its transmission speed which is imperative for video and massive data communication. This led mobile phone technology to embark on the 3G system (Farooq et al., 2013). 3G enabled operators to offer a variety of advanced services. Competition continued between the following evolved technologies of GSM and CDMA: WCDMA and CDMA2000. WCDMA and CDMA2000 were promoted by GSM players and Qualcomm (including its cdmaOne partners), respectively (Seo and Mak, 2010). When 3G services first started in 2001, the transmission speed of the 3G system failed to meet the expectations of service providers and customers. This resulted in the delay and indeterminacy of commercialization of the 3G system, which made GSM the dominant technology until 2005.

For this reason, the real transition from 2G to 3G happened after 3G technology evolved into HSDPA and transmission speed increased considerably. The first HSDPA for commercial use, which launched in 2006, is called 3.5G technology because it is in between 3G and 4G technology.

The economic recession in developed countries that started in 2000 led customers to favor low-priced phones, which stimulated price competition among firms.[3] Giachetti and Marchi (2010) argued that competitive dynamics during the first half of the 2000s (2001–2005) did not fit the classic Abernathy and Utterback model which argues that firms usually focus on process innovation, and not on product innovation, for price cut downs during the shakeout stage. They explained that this “unpredicted upsurge of product innovations” was due to the introduction of the following important new features: multi-message service, color display, and camera phone. However, a dominant feature could not emerge because GSM was still dominant on the technology side. Transition from GSM to a new standard was prevented by the lock-in effect (Kim, 2012; Liebowitz and Margolis, 1995). Entering the stage of maturity during the second half of the 2000s, market share was concentrated in a few firms, which is consistent with the classic Abernathy and Utterback model (Abernathy and Utterback, 1978). The distinctions among the features adopted by manufacturers were insignificant. A multitasking mobile phone became the dominant design due to the technical convergence of different functionalities such as digital camera, MP3 player, internet connection, and so on; a multitasking mobile phone became the dominant design (Giachetti and Marchi, 2010).

5.5. 4G (2010–)

4G is a service based on All-IP which integrates different networks such as a wired network, a mobile network, and a

[2] The Evolution Of The Cell Phone Between 1938 and 2011. http://ginva.com/2011/05/the-evolution-of-the-cell-phone-between-1938-2011.

[3] Early 2000s recession. http://en.wikipedia.org/wiki/Early_2000s_recession.

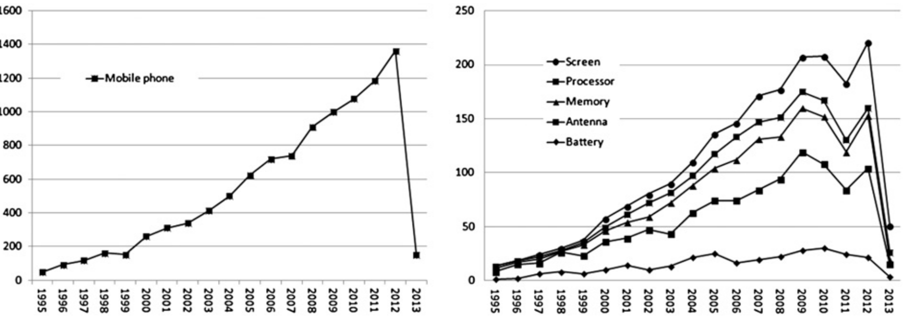

Fig. 3. Number of papers about mobile phone published (left) and about its components (right).

packet data network. 4G technology is more advanced than 3G technology: 4G's maximum download speed is 1Gbps for LTE Advanced technology (Fig. 2) and 4G's data transmission speed can better manage the needs of 3G customers.

LTE, the standard of 4G, is a technology that evolved from WCDMA. Qualcomm, the leader of 3GPP2, ended the development of CDMA2000-based technology in 2008.[4] As a result, competition between 3GPP supporting WCDMA and 3GPP2 supporting CDMA2000 ended with the victory of 3GPP.

5.6. Empirical validation of the hypotheses

In our validation, we considered the five major components of the mobile phone including memory, battery, antenna, processor, and screen. 10,385 papers that contain the keyword "mobile phone" were retrieved from the Web of Science[5] which is widely used for bibliometric research. Among them, 438 papers on memory were retrieved after 1995, 279 papers on battery were retrieved after 1995, 803 papers on antenna were retrieved after 1991, 172 papers on processor were retrieved after 1995, and 346 papers on screen were retrieved after 1997 (Fig. 3; Table 2).

In bibliometrics, the analysis of the number of papers published by year such as the one in Fig. 3 is a technique commonly used to diagnose the status of an industry or to estimate the degree of promisingness for the near future. In Fig. 3, the number of papers continues to increase, which may signify that mobile phone technology will continue to develop in the near future; however, the number of papers cannot be associated with technical innovation or evolution due to insufficient evidence. So, in this paper we introduce a K–L divergence-based method for evaluating technical innovation. In Table 2, we present a method that has the capability of computing the diffusion and critical transition values using only the following three components: battery, memory, and antenna. Our method can be easily and similarly applied to all five components and convergence values.

In Table 2, the first column represents the number of retrieved papers for three components. The second column, the share of feature (ratio), denotes the normalized value of each component ratio. For example, if there is one retrieved paper on memory and there are seven on battery and three on antenna, then the values of $\frac{\text{Battery}}{\text{Antenna}}, \frac{\text{Battery}}{\text{Memory}}, \frac{\text{Antenna}}{\text{Memory}}$ are $\frac{1}{7}(=0.14)$, $\frac{1}{3}(=0.33)$, $\frac{7}{3}(=2.33)$ and their sum is 2.81. Thus, the normalized values are $\frac{0.14}{2.81}(=0.05)$, $\frac{0.33}{2.81}(=0.12)$, and $\frac{2.33}{2.81}(=0.83)$.

The third column represents the diffusion values ($D_{KL}(q||p)$) which are computed using the second column. The third column is composed of three sub-columns. The first sub-column is the diffusion value from year t to year t + 1, and the second sub-column is the diffusion value from year t to year t + 2. The last sub-column is the average value of the first and the second sub-columns,[6] and is used as the resulting diffusion value. For example, in 1995, 0.02 in the first sub-column is calculated as $0.02\log_2\frac{0.02}{0.05}$ (for Battery/Antenna) + $0.13\log_2\frac{0.13}{0.12}$ (for Battery/Memory) + $0.85\log_2\frac{0.85}{0.83}$ (for Antenna/Memory); 0.32 in the second sub-column is calculated as $0.13\log_2\frac{0.13}{0.05}$ (for Battery/Antenna) + $0.33\log_2\frac{0.33}{0.12}$ (for Battery/Memory) + $0.54\log_2\frac{0.54}{0.83}$ (for Antenna/Memory); and 0.17 in the last sub-column is calculated as $(0.02 + 0.32)/2$.

To calculate the critical transition value shown in the last column of Table 2, we need another K–L divergence value from year t + 1 to year t + 2. The critical transition value of 0.13 in 1996, for example, is calculated as 0.02 (from 1995 to 1996) + 0.43 (from 1996 to 1997) − 0.32 (from 1995 to 1997).

Figs. 4 and 5 show the diffusion and convergence values graphically. Fig. 4 shows that the measured values (solid thick line and dashed line) have cyclic peaks and that its regression lines (solid thin line) decrease over time, which is consistent with our first hypothesis. Without this evaluation of the degree of innovation, users would be misled by recent improvements in data transmission speed (Fig. 2) and a variety of newly introduced features, and would mistakenly assume that the mobile phone has been experiencing radical innovations more recently than in the past. Users can see from Figs. 4 and 5 that recent innovations are not as impressive as those in the past. The recent developments in mobile phone technology have failed to exceed researchers' expectations.

Fig. 4 shows the cycles that correspond to the generations of the mobile phone evolution shown in Table 1. The solid thick line represents the diffusion values that were computed using memory, battery, and antenna; the dashed line represents the diffusion values that were computed using memory, battery, antenna, processor, and screen. While both lines correspond to

[4] CDMA2000. http://en.wikipedia.org/wiki/CDMA2000# Liebowitz.

[5] Web of Science. http://thomsonreuters.com/web-of-science/.

[6] The first and second sub-columns are related to a time window for comparison. To smooth data and consider the product life cycle of an aircraft industry, Frenken and Leydesdorff (2000) compared an original product with the subsequent products that were made within five years after the original product was made, and took the average value of them. However, they stated that the length of the time window is not critical to the results. Thus, we use a two-year window of normalization in this paper for simplicity.

Table 2
Diffusion values and critical transition values were computed with three components: battery, memory, and antenna.

Publication Years	No. of papers			Share of feature (ratio)			Diffusion value ($D_{KL}(q\|\|p)$)			Critical transition value
	Battery	Antenna	Memory	Battery/antenna	Battery/memory	Antenna/memory	q at t + 1 from p at t	q at t + 2 from p at t	Average	
1995	1	7	3	0.05	0.12	0.83	0.02	0.32	0.17	
1996	2	13	2	0.02	0.13	0.85	0.43	0.14	0.29	0.13
1997	6	10	4	0.13	0.33	0.54	0.14	0.04	0.09	0.43
1998	8	18	1	0.02	0.30	0.68	0.25	0.14	0.19	0.35
1999	6	17	10	0.13	0.23	0.64	0.01	0.04	0.02	0.12
2000	10	26	10	0.10	0.25	0.65	0.06	0.02	0.04	0.03
2001	14	25	15	0.18	0.30	0.53	0.15	0.02	0.08	0.19
2002	10	37	12	0.06	0.20	0.74	0.22	0.13	0.18	0.35
2003	13	30	29	0.23	0.23	0.54	0.02	0.02	0.02	0.11
2004	21	42	25	0.17	0.28	0.56	0.00	0.05	0.03	0.00
2005	25	49	30	0.17	0.28	0.55	0.06	0.04	0.05	0.01
2006	16	58	38	0.12	0.19	0.69	0.00	0.00	0.00	0.02
2007	19	65	47	0.14	0.19	0.67	0.01	0.01	0.01	0.01
2008	22	72	39	0.11	0.21	0.68	0.00	0.01	0.01	−0.01
2009	28	91	41	0.10	0.21	0.69	0.02	0.02	0.02	0.01
2010	30	78	44	0.14	0.24	0.62	0.00	0.03	0.01	−0.01
2011	24	60	35	0.14	0.24	0.61	0.03			0.01
2012	21	83	49	0.11	0.18	0.71				

the generations of the mobile phone evolution, the correspondence is more evident and the difference between 2.5G and 2G (2001–2004) is more apparent when all five components (memory, battery, antenna, processor, and screen) are used. This fact proves that the year-to-year difference in relative research volumes of each component is correlated with the technological life cycle of a product's core component (in our case, the mobile communication standard). The emergence of widely adopted standards of mobile phones seems to affect changes in R&D portfolios of firms and intensify global competition (Toppila et al., 2009; Allen and Sriram, 2000). Trough points (years) between Figs. 4 and 5 show a two-year gap due to the different definitions of diffusion and convergence, as described above. Diffusion wave (Fig. 4) has trough points when a new generation of mobile phone begins, whereas convergence wave (Fig. 5) has them when the industry is most affected by the birth of a new generation. In Fig. 5, trough points appeared about two years after a new generation began.

There are two kinds of discordances between the expected values and the measured values in Fig. 4: a one-year gap between each start of a cycle and a higher-than-expected value of the third cycle. The one-year gap may be negligible because

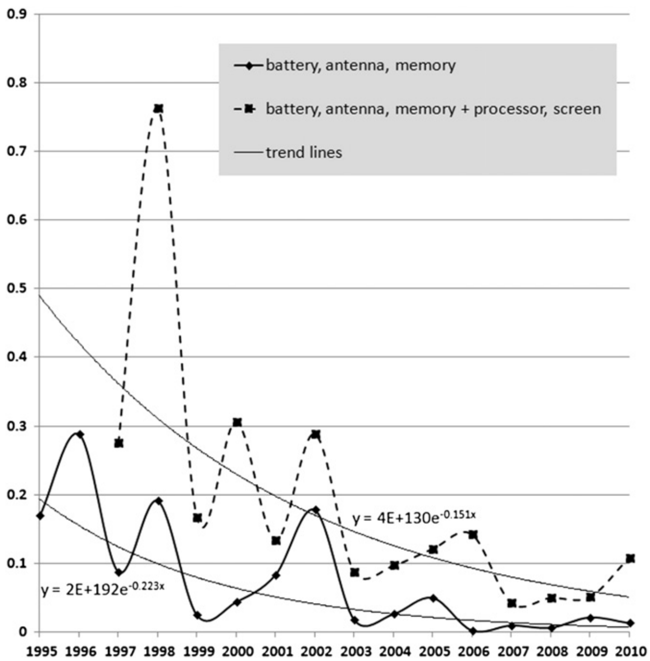

Fig. 4. Diffusion values (K–L divergence) for mobile phones. Papers on screen were published from 1997, so the diffusion values computed using all five components (memory, battery, antenna, processor, and screen) exist from 1997.

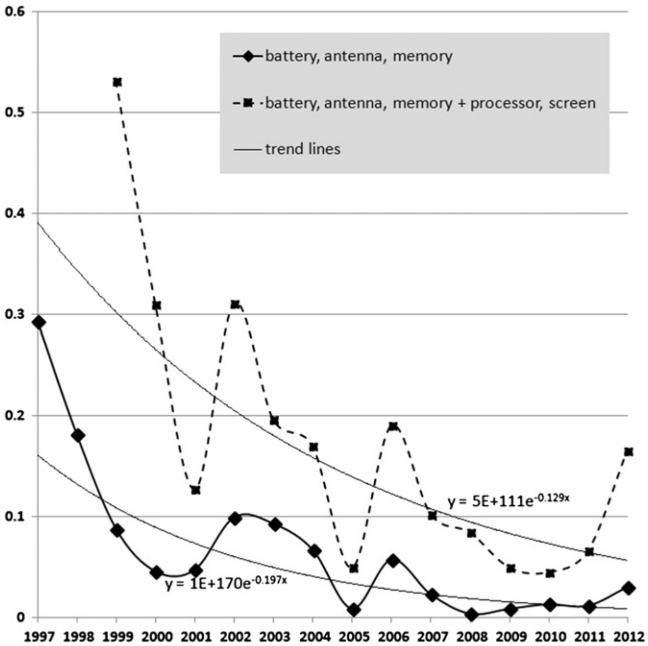

Fig. 5. Convergence values (K–L divergence) for mobile phones. Papers on screen were published from 1997 and a two-year window of normalization is applied, so the convergence values computed using all five components (memory, battery, antenna, processor, and screen) exist from 1999.

there is a small disagreement over the periods of mobile phone generation. Also, the higher-than-expected value of the third cycle can be explained by the unpredicted upsurge of product innovations which is represented as multi-message service, color display, and camera phone (Giachetti and Marchi, 2010).

In Fig. 4, the second generation of the mobile phone evolution (1990–2000) is divided into the first cycle from 1995 to 1996 and the second cycle from 1997 to 1998. This may be due to the fact that the average weight of mobile phones continued to decrease after 1997, while the average talk time and standby time continued to increase until 1995 and then settled at a certain level (Koski and Kretschmer, 2007).

The result of the convergence dynamics (Fig. 5) is in line with the diffusion value. The convergence curve is smoother than the diffusion curve. Due to the slight difference between the calculation methods of the diffusion and convergence values, the cycles on the diffusion curve in Fig. 4 start at the lowest point and end at the highest point, whereas the cycles on the convergence curve in Fig. 5 start at the highest point and end at the lowest point. For example, in Fig. 4, the third cycle starts in 1999 and ends in 2002.

The empirical results summarized in Table 3 compare the measured diffusion and convergence values with the expected values, and identify the types and causes of discrepancies between them.

A critical transition analysis is conducted. The result is presented in the last column of Table 2 and Fig. 6. Two points of critical transition are found: one occurred in 2008 and the other occurred in 2010. Critical transition is deemed to be associated with the emergence of a dominant design. We speculate that 4G's fast transmission speed may cause a technological discontinuity between 4G and 3G. 4G is capable of managing most needs of 3G customers. Therefore, 4G may become a dominant design for mobile phones and has already been a dominant design in some countries. In the case of using all five components including the processor and screen, another critical transition point – when 2.5G started as a transitional generation between analog data transmission and digital data transmission – in 2001 exists.

Table 3
Summary of the results: measured vs. expected.

Cyclic period of measured values			Generation in mobile phone evolution	Type and cause of discrepancy between expected and empirical values
No.	Diffusion	Convergence		
1st	1995–1996	1997–2001	2G (1990–2000)	Diffusion period split caused by intensive weight and size competition from 1997 (Koski and Kretschmer, 2007).
2nd	1997–1998			
3rd	1999–2002	2002–2005	2.5G (2001–2004)	
4th	2003–2005		3G (2004–2005)	Larger than expected diffusion value caused by an unpredicted upsurge of product innovations represented by three features: multi-message service, color display, and camera phone (Giachetti and Marchi, 2010).
5th	2006–2007	2006–2008	3.5G (2006–2010)	
6th	2008–2010	2009–2010	4G (2010 −)	

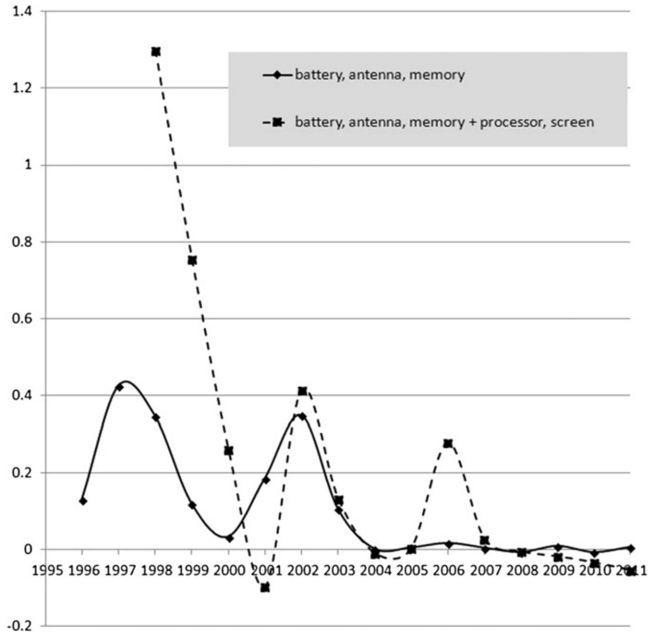

Fig. 6. Critical transition values (K–L divergence) for mobile phones.

6. Discussion and conclusion

We suggested and proved the following two hypotheses: 1) at a macro level, the year-to-year difference in relative research volumes of each component decreases over time as the uncertainty of a product decreases, and 2) at a micro level, the year-to-year difference in relative research volumes of each component is correlated with the technological life cycle of a product's core component. Therefore, we can conclude that bibliometric analysis of research papers can be used as a proxy to measure the degree of uncertainty in a product's technological innovation.

One might point out that the case study is limited in scope because it discusses only one technology. Another might also point out that each industry sector may have unique technological patterns. Nevertheless, we believe that our study lays the foundation for future work on the practical use of bibliometrics to measure the degree of product innovation from the perspective of product life cycle. Assuming that future studies will further validate our method, it could be used to identify the degree of product innovation at low cost.

Our method is useful for cherry-picking promising products (Yeo et al., 2013) among large numbers of candidate products. There are two ways to make our method more effective. First, we can investigate the diffusion (convergence) value of all related products in the industry, and then average the values. This industry average diffusion (convergence) value is compared with the product value of our interest. In other words, the industry average value is used as the baseline to evaluate a product's diffusion (convergence). Second, we can automatically detect subcomponents of a product, which is commonly described as “the automatic extraction of part-whole relation” in computer science; a Natural Language Processing (NLP) tool (Ittoo, 2012; Hage et al., 2006) is needed for this task. Using this tool and not the help of domain experts, a computer can detect subcomponents of a product, and the diffusion values can be automatically calculated for all the candidate products of interest.

There are a few questions that need further research. For example, do the papers about all the components equally contribute to the diffusion and convergence values of a product regardless of the interdependency and constraints of the components? Is our model applicable to products in other domains such as computer science (software), biotechnology, or chemical engineering? Can competition among similar technologies be explained by our method? We plan to address these questions in our future works.

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