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Identification of the technology life cycle of telematics: A patent-based analytical perspective

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ABSTRACT

Identifying technology life cycles (TLCs), particularly TLCs that relate to promising technology, is crucial to managers, technological product investors, and inventors. Telematics technology has gained prevalence in the information and communication technology fields and been increasingly applied. This study determined the current TLC of telematics and investigated using a mainstream technology and development focus at each TLC stage. A supervised assessment method and the indicator pattern of current anchoring technology were employed, and a significance test of the results generated from a curve matching analysis was used to identify the TLC stages of telematics. The results revealed that telematics is in the maturity stage, and the technological focus of each of its TLC stages is distinct. At the maturity stage, telematics emphasizes wireless communication networks and diversified market applications. We assessed the development stage of telematics; governments can refer to this assessment to facilitate strategic development in technological industries.

1. Introduction

Because of the development of the Internet of things (IoT) and popularity of vehicles, transportation is no longer solely focused on transporting people and goods. People's need for transportation safety and efficiency, as well as entertainment experiences for avoiding boredom, have affected technological development. Telematics technology has driven digitalization in the automotive industry and been used to improve driving conditions and enhance road safety. The integration of telematics technology and global positioning system services has shifted the orientation of the automotive industry from production to the provision of knowledge economy services. This study aimed at preliminarily determining the technology life cycle (TLC) of telematics technology as well as the activities and development trends in the field of telematics. The results are expected to serve as a reference for technology portfolio development in the future and subsequent studies.

The investment appeal of technology is determined by its current TLC stage. Typical methods of identifying the TLC stages of technology involve observing the quantitative growth of relevant patent applications and grants. Several empirical studies have indicated that typical patent quantitative growth patterns follow S-shaped curves (also referred to as S-shaped evolutionary paths) or even double S-shaped curves (Andersen, 1999; Chiu and Ying, 2012; Ernst, 1997; Liu et al., 2011; Trappey et al., 2011). Although identifying the TLC of a product or technology by observing an S-shaped curve is feasible, this approach creates a technical problem because it requires statistics regarding all applications in the field of the product or technology (Haupt et al., 2007). Moreover, despite the extremely high data integrity of contemporary patent databases, searching all patents related to particular types of technology in patent databases is difficult or impossible. This problem arises because no definite terms can be used to define and search most types of technology and to collect all patents related to these types of technology from patent databases. Furthermore, patents cannot be precisely matched to particular product technologies even by using the International Patent Classification (IPC) or cooperative patent classification systems.

Moreover, using patent quantity alone to identify TLCs by observing S-shaped curves is an oversimplified method. Therefore, some studies have used multiple patent indicators to determine TLC stages (Alencar et al., 2007; Haupt et al., 2007; Lizin et al., 2013). However, determining TLCs according to multiple indicators sometimes generates subjective assessments. Additionally, defining the time points of TLC stages is difficult and requires a detailed literature review, in-depth case studies, or expert opinions to reinforce the robustness of research data and conclusions.

Therefore, Gao et al. (2013) employed an analogical method and multiple patent-based indicators to estimate the TLC of emerging technologies. Specifically, researchers can anticipate the growth patterns of emerging technologies by using the analogical method to observe those of related technologies. If a strong correlation is found between the two types of technology, then the growth pattern of the emerging type of technology is more likely to be identified. The indicator-based analogical method emphasizes the accuracy of the collected patent data rather than the data quantity, thereby eliminating

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the necessity of a comprehensive investigation of all technology-related patents. Moreover, the study by Gao et al. (2013) aimed to provide a prototype that can be used to determine the technological development patterns of subsequent TLC stages. However, their analogical method requires improvement. Gao et al. (2013) employed the cathode ray tube (CRT) and thin film transistor-liquid crystal display (TFT-LCD) as training technology. However, they did not use a specific method to determine the optimal training technology. Therefore, the present study proposed a novel assessment method. Moreover, Gao et al. (2013) used a nearest neighbor classifier method to analyze TLC by calculating the shortest distance from the test to training points and comparing the test and training technology. However, this method cannot be used to compare two types of technology at particular TLC stages. The present study proposed a more precise classification system.

Based on the limitations identified in the aforementioned studies, this study proposes the following solutions. First, in contrast with previous studies that used a single indicator to determine TLCs (Ernst, 1997; Liu et al., 2011; Trappey et al., 2011), this study predicts the TLCs of emerging technologies by using analogy, which describes the respective patterns of multiple indicators at different TLC stages. Second, although multiple indicators have been employed to measure the life cycles of such technologies – for example, Haupt et al. (2007) proposed hypotheses and conducted a literature review to extrapolate the changes in indicator patterns at different TLC stages – this method is not efficient in delineating the TLC stages unless complemented by a solid theoretical framework. This study aims to address this limitation. In addition, Gao et al. (2013) adopted analogy to predict the TLCs of emerging technologies, eliminating the need for all patent data related to the technologies because the distribution patterns of the patent indicators for an anchoring technology are used to determine the TLC stages of a test technology. Moreover, researchers can prioritize quality over quantity in selecting patent data. This method is also used in the present study. However, Gao et al. neither specified their method for selecting training technologies nor clearly described the similarities at specific TLC stages between training and test technologies (thus, whether comparing these similarities by analogy achieved significance remains unknown). This paper presents empirical approaches to both limitations in the research of Gao et al. (2013).

2. Development of telematics

2.1. Definition of telematics

The development of the intelligent transport system (ITS) resulted in the integration of mobile communications, data transmission, and positioning systems. ITSs have been applied to managing and controlling road and transportation systems, with ITS applications becoming a traffic improvement trend among developed countries. Telematics combines the systems of wireless communications, information management, and in-vehicle computing to allow car owners to use wireless communication functions to exchange and convey information as well as provide drivers and passengers with personalized information services. In recent years, telematics has been a crucial development in ITS fields. “Telematics” is a portmanteau of the words “telecommunications” and “informatics” (Cho et al., 2006). Telematics resulted from the rapid development of wireless communication technology, global positioning systems, and e-commerce. Through the application of onboard units (OBUs) in vehicles, telematics systems facilitate in-vehicle communication and information services. The most crucial features of telematics systems are that they assist people in driving, integrate services, and are service-oriented. Telematics system services are provided by various vendors, such as content providers, content coordinators, software developers, hardware vendors, telecommunication service providers, telematics service providers (TSPs), and telematics system coordinators (i.e., vehicle manufacturers). Through the collaboration of these vendors, telematics systems can be used to provide services (e.g., communication, entertainment, safety, medical, and navigational services) to satisfy user needs. Fig. 1 presents the conceptual framework of a telematics system.

2.2. Future and trends of telematics development

In response to the saturation of the global vehicle market, vehicle manufacturers have explored new markets and developed new products to expand their business scope. In seeking high-value-added products, vehicle manufacturers have transformed vehicles into diversified service platforms. Therefore, vehicles are not only used for transportation but also for providing drivers with additional features to promote driver and vehicle safety as well as mobile communication. Because customers expect vehicles to be equipped with telematics systems, many vehicle manufacturers provide telematics services. As wireless communication technology and information and communication technology (ICT) have evolved, telematics technology has been developed. In addition to some TSPs, which cooperate with vehicle manufacturers, independent TSP vendors also provide telematics services. The cooperation of both types of TSPs as well as telematics technology innovations is the key factor influencing the development of telematics-related industries. This cooperation and innovation drives healthy competition among TSPs and telematics-related industries to develop innovative user-oriented telematics services.

The global telematics market continues to expand and is projected to have a compound annual growth rate (CAGR) of approximately 23% for 2014–2020. Currently, the market penetration is 15% (i.e., of all the vehicle units produced globally, approximately 12% include installed telematics systems [embedded, integrated, or tethered]; according to market trends, this figure is likely to increase by up to 50% by 2020 [IndustryARC, 2014]). The global telematics market is focused on many countries in North America (e.g., Canada and the United States), Europe (e.g., the United Kingdom, France, Germany, and Italy), and Asia–Oceania (e.g., Japan, Korea, and Australia) (Markets and Markets, 2014). Moreover, North America leads the global telematics market, but growth in the telematics market in Europe and Asia-Oceania has been substantial. Therefore, the global telematics market possesses high growth potential.

Telematics systems combine technology from many industries. Therefore, developing telematics systems requires applying and integrating technology from many industries. Because end consumers primarily use telematics systems while driving, these systems should be designed to provide consumers with needed information in a safe and practical manner. Therefore, the key technologies used to develop telematics systems are ICTs, in-vehicle computing technology, human–machine interfaces, and software platforms. Particularly, the rapid evolution of ICTs has produced diverse applications of telematics technology in recent years. For example, although wireless networking environments are highly developed, a new generation of onboard computers was designed, thus connecting driver and passenger smartphones and tablet computers by using wired or wireless high-speed connection interfaces (e.g., Bluetooth, universal serial buses, MirrorLink, mobile high-definition links, and MiraCast devices). Therefore, these onboard devices allow drivers and passengers to access the Internet and operate vehicles, thereby providing additional navigational, media, and networking services. Because of the advances in telematics technology, this study analyzed not only the current TLC stage of telematics technology but also its other TLC stages and the key technologies of each stage, thereby assessing telematics technology development.

3. Methodology

3.1. Determining technology life cycles

3.1.1. By patent data

Since the theory of product life cycle (PLC) was proposed in 1966 (Raymond, 1966), TLCs have been investigated extensively (Andersen,

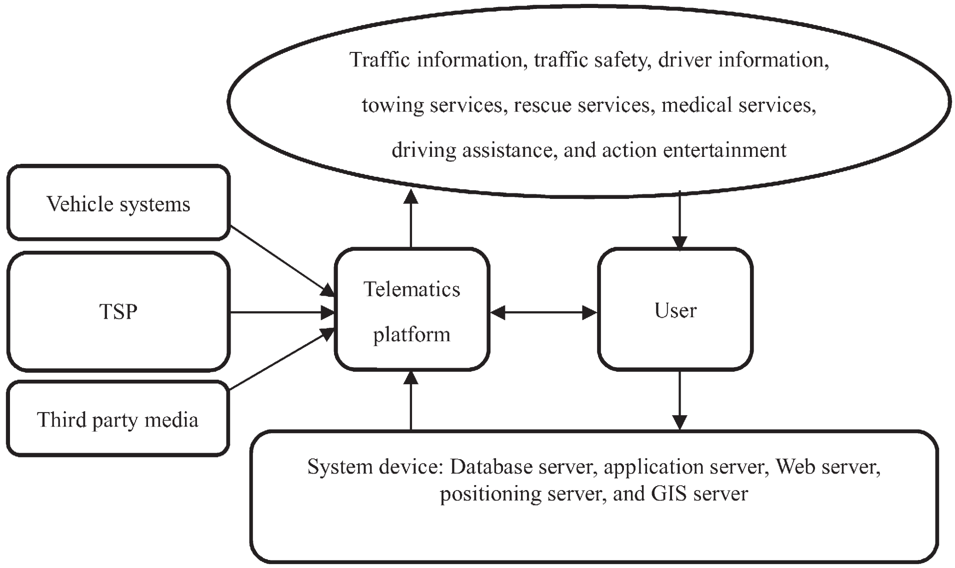

Fig. 1. Telematics system conceptual framework.

1999; Haupt et al., 2007; Lee and Berente, 2013; Taylor and Taylor, 2012). This study focused on applying a technology-forecasting method to judging the current TLC stage of a particular type of technology (i.e., telematics). Levary and Han (1995) summarized many qualitative and quantitative technology-forecasting methods. Because patents are used to protect the inventions and innovations of companies, institutions, and individuals, patents can be used to assess the TLC of inventions. Previous studies have indicated that patent quantity is related to other performance indicators (e.g., productivity or market value) (Chen et al., 2013; Cockburn et al., 2010; Doi, 1996). By analyzing patent data, we can gain unique insight into innovation processes, specifically information regarding particular technical fields and the markets in which innovation occurs. Moreover, patent databases are compiled and managed by patent offices, which examine patents and publish patent information. Although previously restricted to internal use by patent offices, patent data are now accessible to the public through the Internet. Because the cost of using computers has decreased, massive amounts of patent data can be readily accessed. Trappey et al. (2013) indicated that performing patent analyses through government-managed patent databases can reveal technology development trends and provide foundations for technology-related analyses. Many studies have applied patent analyses to estimating technology development trends (Alencar et al., 2007; Lee and Berente, 2013; Lizin et al., 2013; Trappey et al., 2011). Table 1 summarizes recent studies that have drawn on patent data to predict the stages or future trend of technological development.

Most of the studies listed in Table 1 used the S-curve as a patent indicator for TLC analysis. For example, Altuntas et al. (2015) used an S-curve to determine whether each technology candidate was at the growth stage of its TLC. Yoon et al. (2014) estimated current technological maturity ratios for printed electronics through an S-curve analysis. Other authors identified TLCs by using a variety of patent classifications (Leydesdorff, 2015), the proportion of nonpatent references (Lee and Su, 2015), and annual changes in the numbers of patentees and patents (Bu et al., 2014; Fu et al., 2014; Zhang et al., 2012). Still others employed not only patent data but also other indicators such as annual scientific publication rates (Campani and Vaglio, 2015; Järvenpää a et al., 2011; Li, 2015) for TLC prediction.

However, except for the S-curve, the TLC prediction approaches discussed above entail subjective assessments, making it difficult to delineate the TLC stages. Moreover, the S-curve, which predicts the TLC for a technology by its growth curve, necessitates thorough statistics for the patent applications on that particular technology (Haupt et al., 2007), though collating all the relevant data from the existing databases is practically impossible. To address these limitations, this study used analogy to describe the patterns of multiple patent indicators for predicting TLC stages. This method is introduced below.

3.1.2. By a supervised assessment built on prior knowledge

This study employed a quantitative assessment method to quantify patent-based indicators and thus identify the TLC. Using quantitative assessment methods typically requires a large amount of data and mathematical methods for assessing TLC stages. These methods can be classified into unsupervised and supervised assessment methods. Growth curves are typically used in unsupervised assessment methods to analyze TLCs. Specifically, growth curves are used to describe the development path of technology by analyzing patterns of technology evolution according to historical data. Therefore, researchers can evaluate the development pattern of technology by observing the growth curve (e.g., the aforementioned S-shaped curve pattern), thereby forecasting future development trends. However, unsupervised

Table 1
Recent studies that predict TLC stages on the basis of patent data.

Author(s) (pub. year)	Tool(s)/method(s)
Altuntas et al. (2015), Chen et al. (2011), Chiu and Ying (2012), Daiha et al. (2015), Dubarić et al. (2011), Liu et al. (2011), Liu and Wang (2010), Taylor and Taylor (2012), Trappey et al. (2011), Wang et al. (2015), Yoon et al. (2014)	S-shaped curves or double-S-shaped curves
Leydesdorff (2015), Leydesdorff et al. (2015)	Patent classification analysis
Bu et al. (2014), Fu et al. (2014), Zhang et al. (2012)	The number of patent assignees and patent counts
Campani and Vaglio (2015), Järvenpäa et al. (2011), Li (2015)	Patent analysis and bibliometric analysis
Fernald et al. (2013), Lee and Su (2015)	Patent citation analysis
Krafft et al. (2014)	Patent and technological alliances analysis
Ledley et al. (2014), Lizin et al. (2013)	Patent analysis and other related indicators

assessment methods have limitations. For example, the application of single indicators oversimplifies the estimation, and this method requires a complete set of patent data regarding particular technology for validation. Therefore, this study referenced and improved the approach used by Gao et al. (2013) and used a supervised assessment method to analyze the TLC. Supervised assessment methods use supervised classification models or algorithms and analyze available data. These methods are established according to prior knowledge and existing models. Regarding the research procedure, this study first selected an anchoring technology and identified its current TLC stage. In addition, the values of patent-based indicators were extracted for each year. Subsequently, this study used the indicator values obtained by analyzing the experimental technology to conduct a curve matching analysis, thus classifying the patent data and measuring the TLC stages of this type of technology. The research procedure is illustrated in Fig. 2.

3.2. Search strategies and data sources

The most fundamental and challenging task of this study was to select the appropriate anchoring technology. Two criteria were proposed for selecting a technology as the anchoring technology: (1) the most TLC stages completed, thereby facilitating analogies between the indicator patterns of the experimental and the anchoring technologies at all TLC stages, and (2) clearly delineated TLC stages. The second criterion was more difficult to satisfy because delineating the TLC stages for the anchoring technology requires a robust evidence-based approach. This delineation allows the TLC stages of the experimental technology to be specified after analogies between the annual indicator patterns of the experimental and the anchoring technologies have been determined. In this study, the criteria for selecting the anchoring technology were that the TLC of the anchoring technology had to be highly evidence-based and suitable for use as prior knowledge and as an anchoring model for analyzing the experimental technology. Gao et al. (2013) selected the CRT and TFT-LCD as anchoring technologies, and the TLCs of both types of technology were identified using rigorous research methods such as a literature review and questionnaire survey as well as expert interviews. Gao et al. (2013) also identified and described the respective TLC stages of the CRT and the TFT-LCD. Therefore, this study also adopted the CRT and TFT-LCD as the anchoring technologies, in addition to selecting telematics technology as the experimental technology for analyzing a TLC.

The Unites States is one of the largest commercial markets worldwide and has an established patent system with full-text patents since 1976. Moreover, from a technological perspective, the patent system developed by the United States is representative of systems that are used worldwide (Bass and Kurgan, 2010). Therefore, this study conducted patent analyses by using approved and published patent data collected from databases in the United States, specifically from the database operated by the United States Patent and Trademark Office (USPTO). Furthermore, this study applied forward patent citations to avoid unequal citations to selected patents (e.g., patents approved in 2014 are less likely to be cited than those approved in previous years). To ensure data integrity, we selected only U.S. patent data from 1976 to 2013. “CRT,” “TFT-LCD,” and “telematics” are all proper nouns. Thus, the following abbreviations were used in database searches related to finding patent data for the CRT, the TFT-LCD, and telematics: ((TTL/CRT) or (ABST/CRT) or (ACLM/CRT)); ((TTL/TFT and LCD) or (ABST/TFT and LCD) or (ACLM/TFT and LCD)); ((TTL/telematics) or (ABST/telematics) or (ACLM/telematics)). Patent search methods adopted in many patent studies involve entering a selection of search strings into the title, abstract, and claims search fields (Ju and

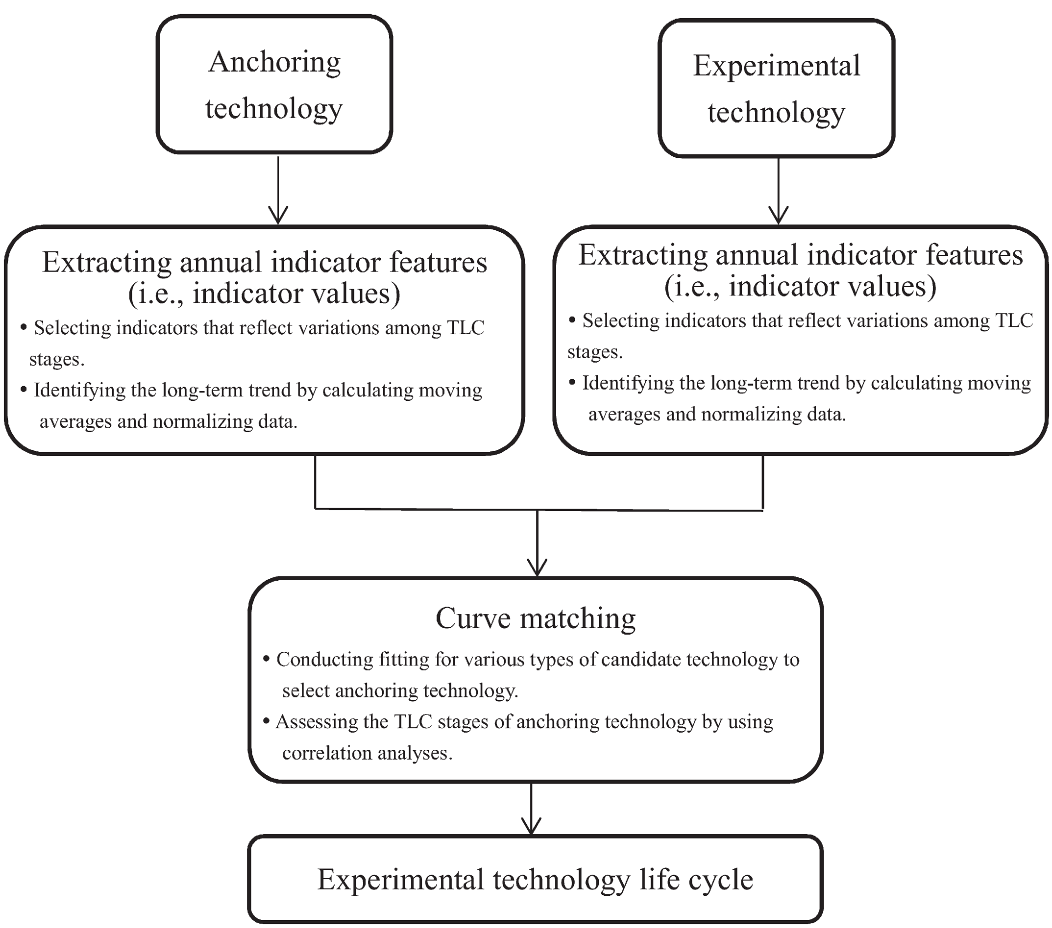

Fig. 2. Research procedure.

Sohn, 2015; Siddiquee and Bhattacharya, 2003; Wang et al., 2010). We obtained 5446 records for the CRT, 1067 for the TFT-LCD, and 639 for telematics.

3.3. Patent indicators of the technology life cycle

3.3.1. Number of patent applications and grants

Many studies have investigated patent number and relative patent growth trends for TLC assessment (Ernst, 1997, 2003; Liu et al., 2011; Trappey et al., 2011). At the emerging stage of a particular type of technology, the number of patent applications is low. However, when this type of technology moves from the emerging stage to the growth stage, basic technological and market uncertainties are eliminated. A wide range of market applications for this type of technology are then developed, thereby accelerating technology development at the growth stage. Therefore, the number of patent applications and grants increase. Subsequently, at the maturity stage, the number of patent applications and grants remains constant, and the technology development enters an incremental innovation stage (Haupt et al., 2007). Finally, during the decline stage, because the potential for product innovation is based on the current product development status, the number of patent applications and grants consistently decreases.

3.3.2. Number of patent assignees and inventors

At the emerging stage, only a small number of pioneer companies are willing to undertake research and design risk, thereby discouraging patent assignees and inventors. When technology development enters the growth stage, the number of patent applications increases steadily until saturation; subsequently, technology development enters its maturity stage, in which technology patent rights are concentrated on a minority of companies and inventors. Thereafter, the number of patent applications consistently decreases, and the technology development enters the decline stage, in which the number of patent assignees and inventors further decreases.

3.3.3. Backward citations

Backward patent citations comprise the citations of a patent in scientific publications and other patents. The fact that scientific publications can be regarded as nonpatent references explains the link between the basic sciences and the patents cited (Meyer, 2000; Zhao and Lei, 2013). This study estimated the differences between basic sciences and patents cited during the development of a particular technology's TLC (Haupt et al., 2007). Because knowledge is cumulative, prior knowledge must be incorporated into new applications during the development of a technology. Therefore, the number of backward citations increases during the growth and maturity stages. However, at the emerging stage, because knowledge of a particular type of technology is inadequate, and the technology application possibilities are unclear, the number of backward citations is low.

3.3.4. Forward citations

When a patent is cited by other patent applications, these citations are referred to as forward citations (Suh, 2015). Patents granted at the emerging stage are cited because they contain information that forms the basis of the new technology. Conversely, patents granted at the growth stage are likely related to specific branches of a particular type of technology and are thus cited by the applications of those branches (Haupt et al., 2007). The number of forward patent citations indicates the degree of knowledge diffusion (Bacchiocchi and Montobbio, 2009; Nemet, 2012) as well as the status and TLC stage of the technology development. Therefore, the number of forward citations differs at distinct TLC stages.

3.3.5. Number of international patent classifications

The number of IPCs represents the classification and diversification of patent applications and implies their technical application scope (Harhoff et al., 2003). The technical application scope of patents granted at the emerging stage may be restricted to specific fields. However, patents granted at the growth stage can be used in a broad range of technical applications. The technical applications of patents granted at the subsequent maturity and decline stages may be restricted to specific fields.

3.3.6. Number of claims

The scope of patent claims is a component of patent applications. The number of patent rights reflects the number of inventions that are protected (Tong and Frame, 1994). Patent applicants can broaden the scope of patented technology by drafting patent applications that include more claims (Sapsalis et al., 2006). Moreover, patent owners can strengthen patent claims by redefining patents and thus obtaining reissued patents; additionally, innovators may increase the scope of the technology to which patents are applied (Bessen, 2008). This study proposed that the number of patent claims increases during later TLC stages. During these stages, technology development matures, and technological knowledge and experiences have accumulated. Therefore, differences in technological development at this TLC stage require identifying more types of technology and obtaining more data to further explain and obtain patent claims.

3.4. Curve matching

3.4.1. Selection of anchoring technologies

This study obtained source patent data regarding 13 patent-based indicators from the USPTO patent database to evaluate the TLCs of the anchoring (i.e., the CRT and TFT-LCD) and the experimental (i.e., telematics) technologies. The source patent data were divided into 1976–2013, 1986–2013, and 1998–2013 periods for the CRT, TFT-LCD, and telematics technologies, respectively. These data were used to form a matrix that encompassed multiple periods and contained multiple indicators. A_1, A_2, and E were used to denote the CRT, TFT-LCD, and telematics original data, respectively, in the matrix (the rows represented 13 indicators, and the columns represented the year).

The first step in this study was data smoothing, which was performed by calculating 3-year moving averages. The moving averages indicated a long-term trend. The original data are shown as follows:

$$\bar{A}_1(i,j) = \frac{A_1(i,j-1) + A_1(i,j) + A_1(i,j+1)}{3}, \quad i \in [1,13], j \in [2,37.]$$

$$\bar{A}_2(i,j) = \frac{A_2(i,j-1) + A_2(i,j) + A_2(i,j+1)}{3}, \quad i \in [1,13], j \in [2,27]$$

$$\bar{\mathrm{E}}(i,j) = \frac{\mathrm{A}_2(i,k-1) + \mathrm{A}_2(i,k) + \mathrm{A}_2(i,k+1)}{3}, \quad i \in [1,13], k \in [2,15]$$

where $\bar{A}_1$, $\bar{A}_2$, and $\bar{E}$ represent the CRT, TFT-LCD, and telematics smoothed data, respectively.

Subsequently, the smoothed data were normalized using the following equations:

$$\mathrm{A}_1(i,j) = \frac{\bar{\mathrm{A}}_1(i,j)}{\mathrm{Max}_j \bar{\mathrm{A}}_1(i,j)}, i \in [1,13], j \in [2,37]$$

$$\mathrm{A}_2(i,j) = \frac{\bar{\mathrm{A}}_2(i,j)}{\mathrm{Max}_j \bar{\mathrm{A}}_2(i,j)}, i \in [1,13], j \in [2,27]$$

$$\mathrm{E}(i,k) = \frac{\bar{\mathrm{E}}(i,k)}{\mathrm{Max}_k \bar{\mathrm{E}}(i,k)}, i \in [1,13], j \in [2,15]$$

where A_1, A_2, and E represent the CRT, TFT-LCD, and telematics normalized data, respectively.

The CRT and TFT-LCD normalized data form the anchoring set Ω ($\Omega \subset \mathrm{R}^{13}$), and the telematics normalized data are considered an

Years	A_{1987}	…	A_{2000}	…	$\min dist(a_j, e_k)$.
E_{1999}	$dist(a_2, e_2)=$ 0.3339	…	1.7170	…	0.2654
E_{2000}	0.0256	…	1.8556	…	0.1034
E_{2001}	0.4380	…	1.6464	…	0.3045
…	…	…	…	…	…
E_{2011}	2.9493	…	1.8349	…	0.8026
E_{2012}	3.2975	…	2.3236	…	0.6254

Note: A denotes anchoring technology; E denotes experimental technology.

The values in the circle are summed, and the two types of anchoring technology are compared with each other according to these sums.

Fig. 3. Selection of anchoring technology.

experimental set Ψ ($\Psi \subset R^{13}$). The CRT training set has 36 anchoring points; the TFT-LCD anchoring set has 26 anchoring points; and the telematics experimental set has 14 test points. The anchoring points a_j and experimental points e_k are defined as

$$a_j = \begin{bmatrix} A(1,j) \\ \vdots \\ A(13,j) \end{bmatrix},\ e_k = \begin{bmatrix} E(1,k) \\ \vdots \\ E(13,k) \end{bmatrix}$$

Moreover, the distances between the test and anchoring points in each year for each of the 13 indicators were calculated.

$$\mathrm{dist}(a_j, e_k) = \|a_j - e_j\| = \sqrt{\sum_{i=1}^{13} (a(i,j) - e(i,k))^2}$$

For each experimental point $e_k \in \Psi$, we computed the distance between e_k and all the anchoring points:

$$dist(a_{j0}, e_k) = \min dist\ (a_j, e_k)\ s.t. a_j \in \Omega$$

Furthermore, the minimum distances between the experimental and anchoring points in each year were summed for both types of anchoring technology. The total distances obtained from both types of anchoring technology were then compared. The type of anchoring technology with the shorter total distance (i.e., a shorter total distance indicated more similarity between the anchoring and experimental curves) was selected as the primary type of anchoring technology (Fig. 3).

3.4.2. TLC stage determination

This study adopted and improved the approach applied by Gao et al. (2013) as well as proposing a method for determining an optimal anchoring technology. In addition, this study employed a curve matching method to classify patent data and correlation analyses to evaluate the similarities between anchoring and experimental technologies at various TLC stages, thus identifying the TLC of telematics.

A correlation coefficient analysis was conducted to compare similarities in indicator patterns between the anchoring and experimental technologies over different years, as summarized in Fig. 4. For example, regarding the data development of the experimental technology indicators in 2006 (E_{2006}), the correlation coefficients of the 13 indicators for the variable E_{2006} in relation to those of the variables A_{1987} to A_{2012} were estimated. The anchoring technology variables that exhibited the highest correlation coefficients in the indicator pattern with E_{2006} were used as equivalent years with E_{2006}. For example, A_{1997} correlated the highest with E_{2006}, suggesting the highest correlation in the 13 patent indicator patterns between the experimental technology in 2006 and the anchoring technology in 1997. Both variables shared the greatest similarities in the distribution patterns of the indicators. Therefore, the 2006 developmental stage of the experimental technology equaled the 1997 TLC stage of the anchoring technology. In other words, the anchoring technology was at the growth stage in 1997, whereas the experimental technology was at the equivalent stage in 2006. This method was adopted to identify the TLC stages in various years of the experimental technology that equaled those of the anchoring technology.

Correlation coefficient estimation to determine the indicator patterns of the experimental and anchoring technologies in different years

Years / Indicator	E_{1999}	…	E_{2006}	…	E_{2012}
Indicator 1	0.0049	…	0.8829	…	0.2780
…	…	…	…	…	…
Indicator 8	0.0031	…	0.2790	…	0.9363
…	…	…	…	…	…
Indicator 13	0.0018	…	0.5816	…	1.0000

Years / Indicator	A_{1987}	…	A_{2000}	…	A_{2012}
Indicator 1	0.0071	…	0.5442	…	0.1484
…	…	…	…	…	…
Indicator 8	0.0045	…	0.1236	…	0.4236
…	…	…	…	…	…
Indicator 13	0.0020	…	0.2604	…	0.7670

Fig. 4. Curve matching and TLC determination.

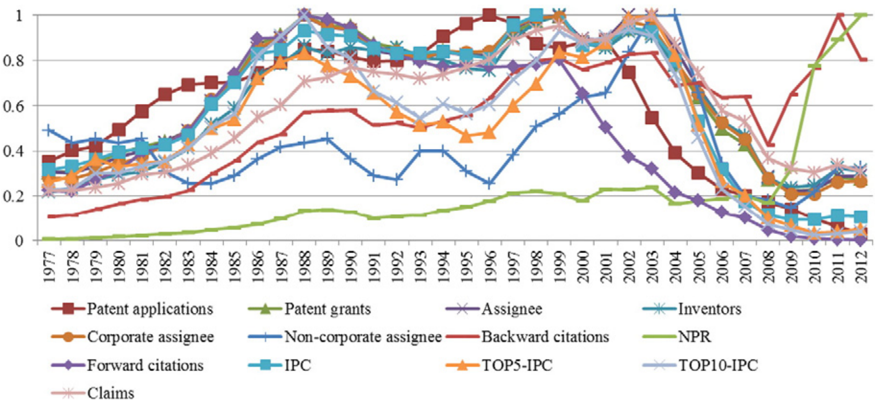

Fig. 5. Data development trends of anchoring technology 1.

Finally, correlation analyses were performed to determine similarities between the anchoring and experimental technologies by year. Because 13 indicators were used in this study, the curves were not defined by the normal distribution. Therefore, a nonparametric statistical method was applied as the primary verification method to calculate the Spearman correlation coefficient. The calculation equation is as follows:

$$r_s = 1 - \frac{6\sum_{i=1}^{13} d^2}{n(n^2-1)}$$

where d denotes the difference between A_j and E_k after ranking.

The aforementioned equation was used to calculate the correlation coefficient between a_j and e_k, and the a_j with the largest correlation coefficient was then determined. The a_j was associated with the corresponding TLC stages. According to the data characteristics of the study by Gao et al. (2013) and the data for both types of anchoring technology obtained from the USPTO database, the emerging and growth stages of the CRT occurred before 1972, and its maturity and decline stages were 1973–2000 and 2001–2020, respectively. After a development of more than 100 years, the CRT is now in its decline stage (Ding, 1997). However, comprehensive patent information from the early stages (e.g., the emerging and growth stages) cannot be retrieved. Therefore, we chose the TFT-LCD to complement the TLC study on the CRT. The emerging, growth, and maturity stages of the TFT-LCD were before 1990, 1991–2007, and 2008–present (Gao et al., 2013).

4. Empirical study

4.1. Data profiles

This study preprocessed the obtained patent data for anchoring technology 1 (CRT), anchoring technology 2 (TFT-LCD), and experimental technology (telematics). Therefore, an eigenvalue was calculated for each year, and the resulting eigenvalues were then used to conduct the curve matching analysis. The data profiles obtained by preprocessing the data are presented in Figs. 5–7.

The inventor indicator exhibited various patterns at different TLC stages. As shown in Figs. 5 and 6, the number of inventors increased before the maturity stage, peaked during the maturity stage, and then declined. The patent grant and corporate assignee indicators also peaked during the maturity stage and then declined. The highest number of backward citations and claims occurred during the decline stage, suggesting technological maturity and accumulation and indicating that additional types of technology require more evidence and further explanation to demonstrate technological difference.

4.2. Curve matching

4.2.1. Selecting anchoring technology

To select the anchoring technology, this study calculated the minimum distance between the experimental points and corresponding anchoring points for each year. The sums of the minimum distances over the years were calculated for both types of anchoring technology: 11.504 (CRT) and 7.739 (TFT-LCD). Therefore, according to the curve

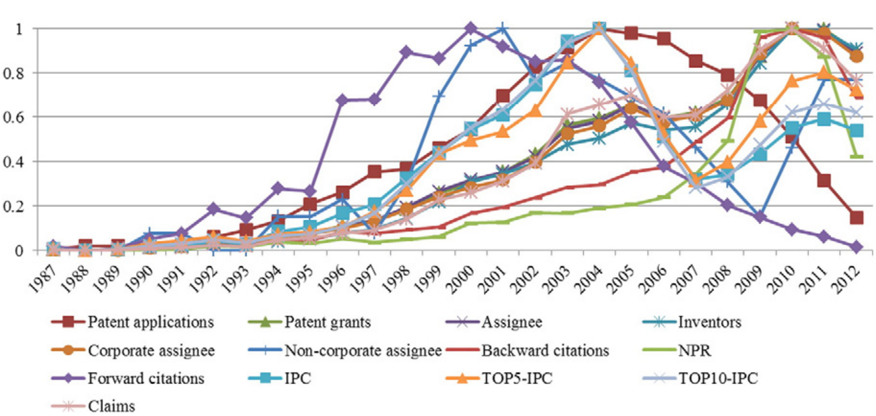

Fig. 6. Data development trends of anchoring technology 2.

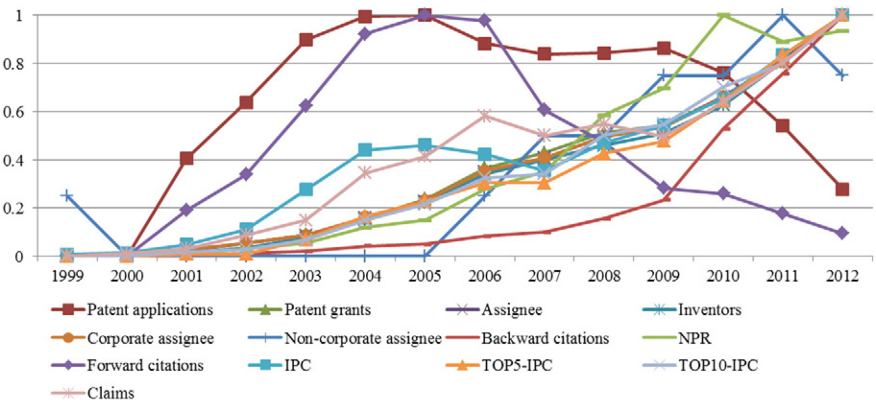

Fig. 7. Data development trends of experimental technology.

matching results for the 13 indicators, the TFT-LCD and telematics had more curve similarity than the CRT and telematics did. Therefore, this study identified the TFT-LCD as the primary type of anchoring technology.

4.2.2. Assessment of curve matching and significance test

This study focused on telematics and evaluated the performance e_k of the 13 indicators for each year. The correlation between the indicator performance of telematics and the indicator performance (a_j) of the TFT-LCD was evaluated for each year, and the year with the strongest correlation (indicating the highest performance similarity) was determined. This indicator performance was also associated with the TLC stages of the TFT-LCD. For example, the performance of the 13 indicators of telematics in 2001 showed the strongest correlation with that of the corresponding indicators of the TFT-LCD in 1997, with a correlation coefficient of 0.720** ($p < .01$). Table 2 tabulates the results of the curve matching analysis.

As shown in Table 2, telematics and TFT-LCD showed a high significance level in the curve matching from 2001 to 2007 and in 2012. This high significance level indicated that telematics entered the growth stage in 2001 and remained there until 2011 before entering the maturity stage in 2012; this was confirmed by a significant curve matching result. The USPTO granted the first TLC patents in 1998, and the r_s showed an insignificant level during 1999–2000. Because of the supervised assessment method used in this study, this insignificant r_s caused the period from 1999 to 2000 to be compulsorily assigned to a stage. Because this two-year period occurred shortly after the patents were granted, this study classified it into the emerging stage. The results of the curve matching analysis for the TLC stages of telematics are summarized in Table 3.

4.3. Portfolios of the technology life cycle stages

This study generated TLC technology portfolios for 639 items of patent data. The supervised assessment results showed that telematics development is currently in the maturity stage. Thus, this study involved the before-growth and maturity stages. Table 4 shows the distribution of the five most common IPC categories in this study. The results shown in Table 3 indicate that telematics technology was mostly concentrated in G01C021 and G06F007 during the emerging and maturity stages. According to the definitions of the IPC, the G01C021 category represents navigational instruments, and the G06F007 category denotes methods of processing data by analyzing the order or content of the data. During the maturity stage, some technologies progressively developed, including G01M017 (testing of vehicles), G06F019 (digital computing or data processing equipment or methods that are adapted for specific applications), and B60Q001 (arrangement of optical signaling, including its mounting or support, or lighting devices, including their circuits). The development of these types of technology has gradually progressed toward maturity. Some technical fields have received attention such as H04W004 (services or facilities that are adapted for wireless communication networks), H04M001 (substation equipment), and G06F017 (data processing systems or methods adapted for administrative, commercial, financial, managerial, supervisory, or forecasting purposes; G06F017 takes precedence over G06F019).

5. Discussion and conclusion

This study adopted the TLC identification approach of Gao et al. (2013), modifying it to propose an assessment method for identifying optimal anchoring technologies. In addition, this study used a significance test to determine the similarity between anchoring and experimental technologies, thereby identifying the TLC. The proposed method was applied to determine the TLC stages of telematics.

The results reveal that telematics is currently in its maturity stage, indicating that many telematics-related types of technology are progressing toward maturity and will soon be used in market applications. According to previous studies, some emerging markets (e.g., Asia–Oceania) possess substantial growth potential (Markets and Markets, 2014). Moreover, telematics systems are an integrative technology industry and require applications and combinations of various types of technology. According to the TLC, the key focuses of distinct

Table 2
Results of the telematics curve matching analysis.

Telematics (year)	1999	2000	2001	2002	2003	2004	2005
TFT–LCD (year)	2006	2010	1997	1997	1997	1997	1997
TLC stage (TFT–LCD)	2	3	2	2	2	2	2
r_s	0.425	0.369	0.720**	0.560*	0.720**	0.780**	0.751**
Telematics (year)	2006	2007	2008	2009	2010	2011	2012
TFT–LCD (year)	1997	2006	2006	1988	1988	2012	2010
TLC stage (TFT–LCD)	2	2	2	1	1	3	3
r_s	0.687**	0.676*	0.423	0.463	0.386	0.330	0.664*

r_s denotes the Spearman correlation coefficient; the emerging, growth, and maturity stages of the TFT-LCD are denoted by 1, 2, and 3, respectively.
* $p < .05$.
** $p < .01$.

Table 3
TLC stages of telematics.

Year	1998	1999	2000	2001	2002	2003	2004	2005
TLC stage	1	1	1	2	2	2	2	2
Year	2006	2007	2008	2009	2010	2011	2012	2013
TLC stage	2	2	2	2	2	2	3	3

Note: The emerging, growth, and maturity stages of the TFT-LCD are denoted by 1, 2, and 3, respectively.

TLC stages differ, and the differences conform to the development trends of global technological industries. The technology portfolios of the TLC analysis show that the maturity development directions of telematics are H04W004 and G06F017. This implies that the series developed by the original equipment progressed to form a wireless network and diversified applications. This trend is consistent with current topics such as machine-to-machine (M-to-M) systems and the IoT, resulting in a considerable degree of correlation and related application development. As wireless information technology has continued to develop, devices other than computers have been capable of connecting to the Internet, including cell phones and iPads. Particularly, using mobile phone applications in telematics systems will be a future development trend (Ernst and Young, 2013). The “M” in “M-to-M” no longer refers only to machines but may also represent “Mobile” or even “Man.” Common wireless network transmission protocols such as Wireless LAN, WiMAX, GPRS, Global System for Mobile Communications, Code Division Multiple Access, Radio Frequency Identification Systems, Bluetooth, and ZigBee have been added to the conceptual framework. Thus, the application of telematics has grown with wireless network development.

Technology industry managers and the government should capitalize on opportunities in communication services and cloud computing to maintain competitive advantages. A new business mode regarding telematics can be generated by connecting mobile devices (e.g., smartphones) to cloud platforms. Many basic types of telematics technology have matured, becoming optimal for market applications. In addition, telematics systems can generate novel applications by integrating them with wearable devices. Wireless network applications that provide vehicle drivers with value-added services will be a future trend in technology. Continual change in ICT allows mobile carriers to develop rapidly. New mobile carriers tend to integrate an increasing number of smart detection and recognition devices, such as signal processing identification devices (e.g., voice command, voice assistant, facial recognition, and somatosensory control devices). Some mobile carriers integrate diversified input-sensing interfaces, which facilitate convenient, safe, and value-added services by using in-vehicle computing and communication functions. How to integrate telematics and portable devices with human–machine interfaces according to current business models and mobile services, thus providing more convenient carrier equipment technology, will be a crucial problem for the government and various industries in the future.

TLC identification is crucial to managers, technological product investors, and inventors, particularly TLCs that relate to promising technology. However, technological development is influenced by many factors such as the rise of killer applications, wild cards, new combinations of technology, and socioeconomic factors. Many external factors can affect technological development, but this is beyond the scope of this study. This study had limitations. First, the dataset was taken from the USPTO database. Although this is one of the most reliable patent databases, some published telematics patents are not included in this database. The results of this study should be interpreted and presented only after considering this limited data source. Second, incorrectly classified patents in the USPTO database may have been included in our study sample. However, because the strict criteria used to narrow the search results in this study, we believe that such patents constituted a small percentage of the total patents examined and that they did not influence the major study results. Third, this study employed two types of anchoring technology to provide sample curve patterns for investigating the TLC of telematics. Applying anchoring technology to determining TLC stages requires considering robustness and evidence-based considerations. Therefore, limited by our inadequate funding and personnel, we chose the CRT and TFT-LCD, which other studies have investigated. Moreover, telematics is an integrative technological application and more diversified. Therefore, in future studies with adequate funding and personnel, other anchoring technologies whose characteristics resemble telematics could be chosen. In addition, expert interviews and case studies should be used to identify TLC stages and evaluate optimal anchoring technology.

Table 4
Distribution of the top five IPC categories.

Rank	Before the growth stage (n = 406)	Maturity stage (n = 233)
1	G01C021 (n = 46)	G01C021 (n = 26)
2	G06F007 (n = 40)	H04W004 (n = 24)
3	G01M017 (n = 32)	H04M001 (n = 19)
4	G06F019 (n = 26)	G06F017 (n = 17)
5	B60Q001 (n = 25)	G06F007 (n = 16)

In summary, this study uses analogies to describe the patterns of multiple patent indicators and to predict the current TLC stages of particular technologies. On the basis of curve matching, the study proposes two approaches to TLC analysis. First, the method presented in this paper for selecting an anchoring technology requires that the proposed anchoring technology have the most TLC stages completed, thereby facilitating analogies between it and the experimental technology and increasing the likelihood of identifying a best-fit between them. Furthermore, to qualify as an anchoring technology candidate, a technology should have clearly delineated TLC stages. Similar to Gao et al. (2013), this study adopts the CRT and the TFT-LCD as anchoring technology candidates because both technologies satisfied the aforementioned criteria. Second, a curve matching analysis is conducted to compare the correlation coefficients of patent indicators between the anchoring and experimental technologies and to determine the significance of these similarities by each year. Based on our research, this study is the first to predict TLCs through curve matching, to verify the fit of various TLC stages of anchoring and experimental technologies systematically and objectively, and to validate their similarities and TLCs through significance testing.

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