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A systematic way of identifying and forecasting technological reverse salients using QFD, bibliometrics, and trend impact analysis: A carbon nanotube biosensor case

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ABSTRACT

Experts have more difficulty identifying reverse salients in R&D because of increasing technological complexity and a shortened technology lifecycle. As an alternative, we suggest a new and systematic method of identifying and forecasting reverse salients using QFD (quality function deployment), bibliometric analysis, and TIA (trend impact analysis). QFD allows users to systematically identify and prioritize reverse salients. An integration of QFD, bibliometric analysis, and TIA makes it possible to specify key performance indicators of reverse salient in order to identify the performance gap between current and market-required performance and to make a probabilistic forecast about when reverse salients will be corrected. Our method will help managers identify a top priority reverse salient, forecast its future, and thus make better R&D decisions with regard to market requirements. A carbon nanotube biosensor technology is used as an example.

1. Introduction

It is important to commercialize emerging technologies (Bhat, 2005) as these reshape industry structure and competition rules through disruptive technological innovation, creating new growth opportunities (Hung and Chu, 2006). For instance, polyimide technology reshaped traditional markets, creating new markets in various industries including film, display, secondary battery, and semiconductor (Mochizuki and Umeda, 2001). However, among emerging technologies, commercialization of some technologies has experienced greater than expected delay.

A number of previous studies have investigated key factors of such delay, focusing mainly on external factors including financing, human resources, absorptive capacity, and collaboration (Cheng, 2012; Holman et al., 2008; Jacobs et al., 2010; Linton and Walsh, 2008; Yanez et al., 2010). However, in early phases of technology development and commercialization, technological obstacles are more important than other obstacles, though non-technological factors become important in later phases (Jolly, 1997).

Despite their importance, there is no systematic method to identify and forecast such technological obstacles. Most previous studies depend on expert judgments (McNeil et al., 2007). However, the increasing technological complexity and shortened technology lifecycle have reduced the reliability of expert judgments, making identification increasingly difficult. As an alternative, bibliometric analysis of large technological data has been proposed but is not used much in R&D practice because it cannot specify obstacles in detail (Alencar et al., 2007; Porter and Detampel, 1995; Van Raan, 2005). Also, since forecasting is based on reliable identification, there has been little effort to forecast when technological obstacles are overcome.

Considering this past research, we suggest a new and systematic method to identify and prioritize key technological obstacles and to forecast when a technological obstacle is overcome in terms of performance. Above all, to clarify the concept of technological obstacles, we introduce reverse salience methodology. A reverse salient (RS) is defined as a subsystem that hinders the full performance potential of an entire system (Dedehayir and Mäkineif, 2008). Since we focus on technological obstacles for commercialization, we define an RS as a technological obstacle that hinders the full market potential of a technology. Note that market potential can be fully exploited when various market requirements are met by technologies. Thus, in our research, operational criteria and measures of RSs are derived from key market requirements, comprising not only externally imposed criteria such as regulation, but also internal technological performance measures. However, operational measures might vary with technology and relevant market and thus can include technological architecture, performance standards, and

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other measures. Overall, an RS is useful to define, evaluate and prioritize key technological problems.

Our method consists of three phases. In the first phase, using QFD (quality function deployment), we identify, evaluate, and prioritize RSs. In the second phase, key performance indicators of top priority RSs are defined. Through bibliometric analysis of journal papers and patents, we plot past trends of key performance indicators and identify the gap between current and desired performance for commercialization. Finally, using TIA, we perform a probabilistic forecast of achievement of the RS solution and the desired performance. TIA is a forecasting technique to create a range of future values by reflecting combined effects of important future events (Agami et al., 2009).

As an illustrative example, the carbon nanotube (CNT) biosensor is selected. The CNT is an emerging technology that can be applied to various fields, including films, solar cells, and sensors (Spitalsky et al., 2010). However, its commercialization has been limited in some high-strength products and has occurred later than industrial experts expected. Also, there is no consensus on the top priority technological RS for R&D and commercialization (Endo et al., 2008). Among various CNT-based products, a CNT biosensor typically has these problems and thus is selected.

This paper proceeds as follows. In Section 2, we review previous RS studies and existing forecasting methods, positioning our approach in the context of current literature. Then, the research framework and methodology are explained. Subsequently, an empirical analysis of the CNT biosensor is provided. Finally, we end with some discussion and conclusions.

2. Literature review

2.1. Reverse salients

In contrast with a unitary view on technology systems, a systemic view perceives a technology system as consisting of multiple interactive subsystems. If a certain subsystem cannot deliver the necessary level of performance compared with other subsystems, it can hinder the advance of the entire technology system while limiting overall performance due to the continuous interaction among subsystems. A technology system cannot make advances unless the technological obstacle is solved (Hughes, 1983). An RS can be defined as such a subsystem.

Using reverse salience, previous studies have investigated the evolution of technology systems and the role of RSs. Hughes (1983) introduced the concept of RSs to analyze a direct-current electric system generator. Similarly, Murmann and Frenken (2006) decomposed an automotive technology system into technological sub-systems, including the body and engine, and identified technological RSs. Similarly, MacKenzie (1987) identified technological RSs of a ballistic missile technology system. Others suggested external RSs including the consumer, supplier, and law (Bijker et al., 1987; Takeishi and Lee, 2005).

RSs are useful to understand not only stable, but also dynamic technology systems. For instance, Dedehayir and Mäkineif (2008) analyzed dynamics of changing RSs in personal computer (PC) games. Between the two subsystems, the central processing unit (CPU) and graphics processing unit (GPU), the RS changed. They subsequently calculated the different speeds of technology development and forecasted future RSs (Dedehayir and Mäkinen, 2011). However, with their approach, they had difficulty identifying RSs of a sophisticated technological system comprised of many subsystems because they depended on intuitive judgments.

Mulder and Knot (2001) divided a PVC technology system into lower-level subsystems, identified RSs at the level not only of a subsystem but of related subsystems and thus attempted to systematize identification. Further, they tried to identifying changing RSs as the technology system changed over time. However, most problems of expert judgments, such as subjective bias and bounded knowledge, remained unsolved. As shown in Table 1, there have been no efforts to overcome such weaknesses for ex-ante and structured identification of RSs. RS forecasting is at a very early stage, with only one previous study using simple extrapolation. Addressing these issues, our approach aims at ex-ante and structured RS identification as well as RS forecasting.

2.2. RS identification and forecasting methods

As noted above, ex-ante and structured identification of RSs might be one way of making the concept of the RS more useful and relevant for researchers, technology developers and managers. Also, the relationship between market requirements and RSs should be considered to prioritize RSs in terms of technology commercialization. As for forecasting, it should be noted that experts have been struggling to make a reliable time forecast regarding the performance of RSs. It has frequently been observed that the performance increases of RSs were slower or faster than expected (Lo et al., 2012). Quantitative methods based on historical data can be used to minimize such time errors and thus produce better forecasts by extrapolating past data into the future. However, these methods cannot consider the effects of future uncertainties that can deflect the future trend. Considering this information, there is need for a forecasting method that can minimize time scale errors and reflect future uncertainties.

Based on our methodological requirements, we select existing methods that fulfilled more than two of our requirements, as shown in Table 2. Trend extrapolation is included because it was used in recent RS forecasting research by Daim et al. (2013). Advanced expert-based methods including Delphi, scenario, and technology roadmap have the advantages of ex-ante and structured identification and future uncertainty consideration but have difficulty specifying technology-market relationships and reducing time errors (Linstone and Turoff, 2011; Meyer and Winebrake, 2009; Carvalho et al., 2013). Also, trend extrapolation is too simple to reflect future uncertainties.

MCDM (multiple criteria decision making) methods meet the requirements for RS identification. However, quantitative MCDM

Table 1
Previous RS studies.

Previous study	Technology system	RS type	Method	Ex-ante RS identification	Structured RS identification	RS forecasting
MacKenzie (1987)	Missile	Technological	Expert judgment	X	X	X
Mulder and Knot (2001)	PVC plastic	Technological Social	Expert judgment	X	X	X
Takeishi and Lee (2005)	Mobile music	Technological Social	Expert judgment	X	X	X
Murmann and Frenken (2006)	Automobile	Technological	Expert judgment	X	X	X
Dedehayir (2009)	PC game	Technological	Expert judgment	X	X	X
Daim et al.(2013)	Video game console	Technological	Expert judgment	X	X	Extrapolation