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Exploring Technology Forecasting and Its Implications for Strategic Technology Planning

by

Yonghee Cho

A dissertation submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Technology Management

Dissertation Committee: Tugrul U. Daim, Chair Timothy R. Anderson Robert Fountain Jisun Kim

Portland State University 2018



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Abstract

As the importance of R&D has been growing in economic growth, the accountability and effectiveness of R&D program are highly emphasized. Especially, in times of economic downturn, the evaluation of performance in a firm is needed to justify R&D investment. In response, various attempts have been made to improve success rates of R&D projects, gain competitive advantage, and achieve a firm's growth in profitability. In particular, in industries where technological innovation is significant, strategic technology planning and R&D capabilities may be the lead ones in defining the dynamic capabilities of a firm. In addition, technology forecasting (TF) in technology planning is a crucial step to follow before developing technologies/products/processes in need.

In this regard, researchers have an abiding interest in enhancing methods to forecast emerging technology, while practitioners have a considerable interest in selecting appropriate tools to apply in their field for better forecasting results.

Nevertheless, so far it is not well documented how appropriately the current research responds to this need. Thus, a thorough review on TF techniques is conducted to help researchers and practitioners capture methodologies in a tangible way and identify the current trends in the TF arena. Moreover, there is still a lack of clear guidance as to where and how particular TF methods are useful in strategic planning based on technology characteristics as well as the nature of industry. The purpose of this study is to enrich the stream of research on TF activities in a firm for practitioners and



researchers, a unique context where TF could lead to technological innovation. This research offers a classification of the approaches, and presents technological, industrial, methodological, and organizational aspects of TF methods that are inherent in TF activities. Furthermore, this study provides empirical evidences to support organizational and managerial implications regarding TF activities associated with technology planning in a firm. Research findings in regimes of technological change suggest insights on technological, organizational, and managerial processes within the firm.

On the other hand, research on the effects on business performance of "best practices" of strategic planning, which enable firms to articulate their plans to develop, acquire, and deploy resources for accomplishing firms' financial growth, has so far ignored the roles of strategic technology planning associated with TF. In this regard, this study explores a set of indicators, discusses, and presents the findings from the literature in such a way that they become useful for researchers or managers who are in charge of measuring the R&D performance and business performance from innovation activity. Next, this research tested the hypothetical framework proposed not only to provide a current snapshot of how firms across industries implement best practices in strategic technology planning, but also to improve the effectiveness of strategic planning. The results present the positive linkages between TF, technology planning, and superior business performance. The findings in this research help policy makers, universities, research institutes/national labs, and companies to enhance their decision making process on technology development.



Dedication

To my family (Joy, my wife, Joseph, Grace, and Esther, my children)

Glory to our God!

Glory to our King!

Glory to our Lord!

Ruler of Everything



Acknowledgments

This dissertation would not have been done were it not for the guidance and valuable comments from the committee. First, I would like to express my deep gratitude to Dr. Daim who continuously guided me through the completion of this research. His consistent support in many ways helped me go through the long process to finish this dissertation. Dr. Anderson also gave me critical comments on analytical problems in this research and helped me finalize my dissertation in every detail. Dr. Fountain, as a professor of Statistics Department, helped me develop the survey instrument and cover statistical issues through his classes and research guidance during my research for this dissertation. Finally, Dr. Kim also supported and guided me to go through this process and to bear this fruit of research. I benefited greatly from the input and comments by all dissertation committees, for they enriched my views about what I need to look at research problems. Committee whose good advice I did not follow should know that I tried to incorporate their thoughtful feedback, and where the comment was consistent and clear, I did.

I would like to express my special gratitude to all survey respondents who provided their feedbacks and valuable inputs for this research. Without their help and insights, I would not have been done. I owe a special debt of gratitude to them. I want to express my sincere thanks to my colleagues, Chih-Jen Yu, Edwin Garces, João Ricardo Lavoie, and Rafaa Khalifa at ETM department, and expert groups for valuable comments and feedbacks on research contents and constructs, without whose expert advice, reviews of survey design, and other assistance this dissertation would never have been possible.



Moreover, I would like to express my sincere thanks for the encouragement and prayers of people that I have known in my life, especially Hanna Jung.

Last but not least, this dissertation would not have been done were it not for the encouragement of my family's support. This dissertation is dedicated to my beloved ones in my life: Heejoung Kim, my soulmate and wife, Joseph, Grace, and Esther, my children. They are thanked for their love, unwavering support, understanding, and patience that only family can give.

Any errors are my sole responsibility.

The road less traveled.

Stay hungry, stay foolish in Truth!



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Chapter 1 Introduction

With the rapid change of technology platform, the endeavor to grasp the performance potential of current and emerging technologies has brought attention to the significance of technology forecasting (TF) in strategic planning. In practice, TF is inevitably needed to help firms to identify and assess opportunities and threats in their competitive business environment, allocate resources in R&D portfolio and new product development, and develop strategies in creating strategic alliances such as licensing in/out and joint ventures. Thus, a thorough review on TF techniques is conducted to help researchers and practitioners capture methodologies in a tangible way and identify the current trends in the TF arena.

On the other hand, little research has been done to identify how a firm's TF activity impacts its performance. Thus, this research provides a current comprehensive snapshot of how firms across industries implement best practices in TF to facilitate organizational functions and strategic technology planning. Moreover, this study offers broader conclusions regarding the relationships between TF, technology planning, research and development (R&D) performance, and business performance.

Historically, TF has been of much interest to governments and research institutions, and such institutions have employed it to plan technology policy for R&D programs and to advance their agendas. Public organizations were the early adopters and developers of various TF and foresight methods and practices. However, beginning with the 1960's, the primary users of TF shifted from government to private companies. As Erich Jantsch and Robert Ayres noted in the late 1960s, companies at the time began to focus on the integration of technological forecasting with long-range planning, and



the implications for organization structure and operations [1][2]. Thereafter, corporations have increased their use of long-range planning as management began to recognize the importance of a long-term strategy in responding to increased competition among firms [3][4][5], the speed of technological change [6], and particularly the fast-paced advancement in information technology [7].

Long-range planning refers to formalized activities involved in setting long-term goals for business and defining specific plans to achieve these goals [8]. Most firms have some framework of formalized planning, and forecasting is one of the essential inputs to such planning [3]. Several studies underscore the need and the role of TF in strategic planning [9][10][11]. With the rapid change of technology platforms, and the increasing intersection between companies and other functions such as government policymaking, TF activities such as the technology roadmap, business/technology strategy, and information technology (IT) have gained significance.

TF is necessary to help decision makers identify and assess opportunities and threats in the firm's competitive business environment [9], and to guide planning when creating new venture or strategic alliances such as licensing and joint ventures [12][13]. Moreover, TF is indispensable to corporate planning groups and R&D laboratories, not only for the purpose of formulating business and technology strategy, but to allocate resources in the R&D portfolio and to shape the direction of new product development [14].

Proactive TF is necessary to transform individual behavior, organization, economy, society, and culture in a turbulent world. Government and companies should strive to anticipate how technology developments will impact future business



environments and society. Since there is a high degree of uncertainty associated with technological change, it is imperative that organizations periodically reassess the viability of R&D projects during the planning process at certain milestones.

In order to implement TF effectively, it is vitally important to understand how technological change occurs. Kuhn suggests that the normal development path of scientific knowledge is heavily selective, often centered on whatever dominant framework to which the leading scientist in the field may adhere [15]. This so called "technology trajectory" often defines the direction of technological evolution [16]. Technological development in this vein is inherently based upon the accumulation of knowledge—a cumulative process. On the other hand, disruptive (discontinuous) technological innovation is different from technological development occurring on a technology trajectory. Discontinuous technological change can be defined as scientific discoveries that breakthrough the usual product/technology capabilities and create an entirely new market through them [17][18][19]. It is very crucial to forecast disruptive technologies for firms to maintain profitable R&D investments and create feasible business plans for commercialization.



Chapter 2 Research Background and Literature Review

A variety of TF methods have been developed and applied to various industries and organizations, suited to different purposes. Few studies, however, have attempted to explore the collective implications of technology forecasting to an organization's business performance. This study sheds a light on the best practices of TF implementation and analyzes how TF functions within organizations. In particular, this study focuses on how systematic forecasting helps businesses make better strategic decision.

Today, organizations are facing an increasingly complex and changeable external environment. In such an environment, being well-informed about technological changes has the potential to dramatically alter the effectiveness of an organization's technology management [20][21][22]. Consequently, establishing systematic technology innovation management, capable of predicting technological change at the pace of innovation, is necessary for business success in a tornado world market. To date, many efforts have been made to determine the governing principles of technology management and to integrate business management with technology management [20]. A number of studies recommend that a company should align R&D strategy with business strategy in the areas of technology development, manufacturing, sales and marketing, personnel, finance, and accounting. The first step to establishing an appropriate R&D strategy, however, is to forecast the technological direction of the industry.

In the midst of increasing business uncertainty and complexity, firms have invested in environmental scanning efforts, such as bibliometric/patent trend analysis and market analysis, to identify increasingly diversified needs of customers, establish



technology initiatives responsive to those needs, and improve their future position. In the last four decades, especially after the widespread availability of information technology (IT), researchers have developed many different approaches to using sources of information and information tools such as patent databases, journals, and research awards, to comb through vast amounts of data and extrapolate trends. Figure 1 presents the chronological tree of TF methods.

Methodologies in technology foresight and technology forecasting are not fixed. Certain TF methods are employed concurrently to predict technological changes or innovations, but others are not. For example, a combination of approaches and methods is required to improve the effectiveness and accuracy of forecasting, since combining multiple techniques enables forecasters to analyze various perspectives (organizational, technological, economic, political, personal, social, and environmental) [23][24]. TF experts maintain that, in order to respond effectively to rapid social change and the increased complexity of state-of-the-art science, one of the next generation of forecasting approaches must combine exploratory and normative forecasting methods [25]. Forecasting done for exploratory or opportunity-oriented purposes may interact with forecasting done for normative or mission-oriented purposes [13]. As a contrasting example, however, it would be theoretically inappropriate to use composite methods to solve forecasting problems that are of a more practical nature. In such instances, the conflicting assumptions inherent in the two or more types of forecasting may lead to an unusable answer. The proper selection of TF methods depends on the nature of the technologies [26]. The first task in forecasting is to choose the forecasting method that is most appropriate to the analysis and the characteristics of the field of technology



being analyzed—such as whether the technology is disruptive versus incremental. Selecting a suitable method would depend on several factors, including the level of uncertainty in the technological field, data availability, difficulties inherent in the technology, or the availability of funding for R&D.

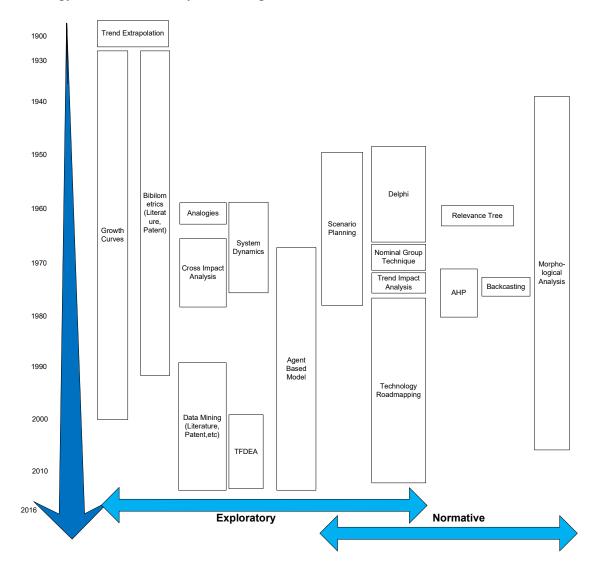


Figure 1 The chronological tree of technology forecasting techniques



2.1. The Concepts of Technology Forecasting and Technology Foresight

There is little agreement over the meaning of the terms, "technology forecasting" and "technology foresight", and there has been relatively little effort to clarify the similarities and differences between the two terms [25]. Historically, the term "technological forecasting", coined around mid 1940s, has been used more often and for longer in literature than the term "technology foresight", coined in the early 1980s [27]. As these two terms have been used interchangeably and inconsistently in the literature of the last decade, it is important to conduct a comprehensive review of the concepts historically associated with these terms and to foreclose potential misinterpretations of these two concepts in future research, by clarifying their meaning.

Technology forecasting is different from social forecasting, economic forecasting, market forecasting, financial forecasting, transportation demand forecasting, and weather forecasting, but in some contexts, these various concepts may intertwine [28][29]. To define TF, we can consider the definition of "technology" and "forecasting", respectively. What is technology? Webster's Dictionary defines it as "[t]he practical application of science to commerce or industry." At times, "technology" can refer to a concrete physical object. One might be accustomed to thinking that the definition of technology does not include a human being's abstract knowledge. However, Quinn defines technology more precisely as "not a single immutable piece of hardware or bit of chemistry, but also knowledge of physical relationships—systematically applied to the useful arts" [29]. To "forecast" is to predict how something will develop. Forecasting normally ends with the identification of possible futures.



As more than the sum of its component parts, the definition of "technology forecasting" varies and covers a wide range of activity. In 1962, Lenz, one of the pioneers of technological forecasting, defined technological forecasting as "the prediction of the invention, characteristics, dimensions, or performance of a machine serving some useful purpose. . . . The qualities sought for the methods of prediction are explicitness, quantitative expression, reproducibility of results, and derivation on a logical basis" [30]. In 1967, Jantsch, who was a consultant to the OECD, defined technological forecasting as "the probabilistic assessment, on a relatively high confidence level, of future technology transfer" [13]. This definition focused more on the technology transfer perspective. According to Bright, technology forecasting refers to "systems of logical analysis that lead to common quantitative conclusions (or a limited range of possibilities) about technological attributes and parameters, as well as technical-economic attributes" [1]. Cetron describes technological forecasting in more detail as "prediction with a level of confidence of a technical achievement in a given time frame with a specified level of support"[31]. Martino defined technology forecasting as "a prediction of the future characteristics of useful machines, procedures or techniques," explaining that "technology is not restricted to hardware only, but may include 'know-how' and 'software'" [32]. This definition highlights that technology includes practical application and that it is not purely scientific knowledge. Ascher defined technology forecasting as the effort "to project technological capabilities and to predict the invention and spread of technological innovation..." [33]. In addition, Millett and Honton expand the concept of technology forecasting as "the process and result of thinking about the future, whether expressed in numbers or in words, of



capabilities and applications of machines, physical processes and applied science" [34]. This definition includes business environment and corporate concerns as well as technological performance.

In summary, technology forecasting refers to the analysis and the evaluation of performance parameters, timing of advancements, new concepts, products, processes, market penetration, and sales in a given time frame with probability statements, on a relatively high confidence level, which anticipates opportunities and threats from technological changes in order to provide for more well-informed R&D decision-making.

The main objective of technology forecasting is to support decision making as well as R&D and business planning. As Swager has identified, technology forecasting play five roles: identifying policy options, aiding strategy formulation, identifying program options, selecting programs for funding, and selecting opportunities for investment [9].

In addition to the term "technology forecasting", the term "technology foresight" has also come into common usage. Initially, foresight and forecasting were used interchangeably [35][27], but, there is now a real difference in the understanding of forecasting as contrasted to foresight [36]. The term "technology foresight" or "national technology foresight" has increasingly been used to signal the role national governments are playing in identifying socially desirable technologies [25]. In 1985, Joseph Coates identified foresight as "the overall process of creating an understanding and appreciation of information of varying degrees of credibility, completeness, and technical and scientific soundness generated by looking ahead" [37]. In 1995, Ben



Martin defined technology foresight as "the process involved in systematically attempting to look into the longer-term future of science, technology, the economy and society with the aim of identifying the areas of strategic research and the emerging of generic technologies² likely to yield the greatest economic and social benefits" [38]. Since the 1990s, technology foresight has been actively and broadly implemented in Europe. In some European context, networking and cooperation in identifying future options is as—in some cases even more—significant than the tasks of forecasting [36]. Technology foresight goes further than forecasting, encompassing aspects of networking and the preparation of decisions regarding the future [36]. Foresight broadens the scope of attention to a national scale. Foresight not only looks into the future by using all instruments of futures research, but includes utilizing implementations for the present [36]. The ultimate objective of foresight is to ensure that areas of science and technology that are likely to yield future socio-economic benefits such as health, quality of life, environmental protection and contributions to culture are identified promptly [38]. Table 1 provides a summary of the distinctions between technology forecasting and technology foresight.

Generic technology' is defined as "a technology the exploitation of which will yield benefits for a wide range of sectors of the economy and/or society" [559], p.51.



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¹ 'Strategic research' is defined as "basic research carried out with the expectation that it will produce a broad base of knowledge likely to form the background to the solution of recognized current or future practical problems" [558], p.4.

Table 1 Technology forecasting vs. Technology foresight

Term	Definition	Characteristics	Elements	Type of Affiliation (Inception)	Nation	Citation
Technology Forecasting	A prediction of the future characteristics of useful machines, procedures or techniques i.e., technology is not restricted to hardware only, but may include "know-how" and "software	- Prediction, not necessarily assessments More quantitative than qualitative No information about consensus necessary Less dependent on opinions Identification of possible futures.	1) The time of the forecast 2) The technology being forecast 3) A statement of the characteristics of the technology 4) A statement of the probability associated with the forecast	1. Government 2. Academia 3. Industry	US (1937), EU[Netherland (1949), France (1961), Germany (1964), Italy (1965), Switzerland (1965), Austria(1966)], Israel (1954), Canada (1960s), UK(1963), Japan (1975), China (1985), South Korea (1990s), India(1997)	[1][32] [29][13] [36][39] [40][26]
Technology Foresight	The process involved in systematicall y attempting to look into the longer-term future of science, technology, the economy and society with the aim of identifying the areas of strategic research and the emerging generic technologies likely to yield the greatest economic and social benefit	- Outlook, based on a bundle of systematic and comprehensive processes for looking ahead, with criteria for assessments More qualitative than quantitative Finds out if there is consensus on themes Very dependent on opinions Many possible futures, neither too general nor too detailed Process must be public.	1) Direction-setting 2) Determining priorities 3) Anticipatory intelligence 4) Consensus generation within research community or externally among research funders, performers and users 5) Advocacy for a new research initiative 6) Communicati on and education within the research community	1. Government 2. Academia 3. Industry	Japan(1971), US (1980s), Canada(1980s), EU[Netherland s(1988), Germany(1991) , France(1994), Spain(1995), Italy(1995), Hungary(1997), Austria(1997), Norway(1998), Sweden(1998), Portugal(1999), Denmark(2000) ,Finland(2001)] , New Zealand (1992), UK (1993), Australia (1994), South Korea (1994), China (2002)	[25] [36]–[38] [41]–[51]

2.2. The Subsets of Technology Forecasting

2.2.1. Characteristics of Technology Forecasting

Technology forecasting consists of subset elements such as a certain future time span, technological change, continuous range of characteristics in applications, and a



statement of the probability associated with the technology [32]. Technology forecasting does not necessarily need to predict the exact form of technology dominating in a given application at some specific future date, since technology forecasting aims to provide the evaluation of the probability and significance of various possible future developments in order for managers to make better decisions [29]. In most cases, technology forecasting is wrong. Technology forecasting, however, is valuable to give guidance for the direction of promising technology development. The value of technology forecasting lies in its usefulness for making better decisions, not in its coming true [32]. Technology forecasting, in other words, is typically only partially correct and cannot include all exact future forms. Technology forecasting strives not only to identify research and knowledge gaps to find the right path to reach goals, but to search ranges of environment that may be encountered in the future.

2.2.2. Assumptions of Technology Forecasting

One of the most significant tasks in technology forecasting is to decide on the right assumptions and appropriate methods for a given situation, so as to predict the right technological change in a certain future, since the methods employed inevitably affect technology forecasting results [26][52]. The selection of methods mainly affects the accuracy and reliability of technology forecasting. If the assumptions are inaccurate, the prediction would go a wrong direction. Many forecasters attempt to resolve the predictive challenges of technology forecasting by increasing the sophistication of their methods and improving the quality of data. When a technological landscape is volatile, however, merely employing increasingly complex methods to capture small analytical gains is likely to be futile. In addition, forecasting requires a technique that is suited to



the characteristics of a certain technology, but not all problems in technology forecasting are so easily categorized [26]. As a further challenge, only data from the past and present is available. One of the mistakes of technology forecasting is to assume that the future is fixed or pre-determined. Furthermore, mistakes in trend projection most often arise out of the assumption that the future will simply be an addition or subtraction from the present, based upon the assumption that technology will follow past trends. It ignores the effects of unprecedented future events. Therefore, most problems in forecasting are caused not by a lack of sophistication but by drawbacks inherent in the process of technology forecasting [53].

2.2.3. Technological Trajectory vs. Discontinuity

For the appropriate use of technology forecasting, it is vitally important to understand how technological change develops and happens. Kuhn describes that the normal development path of scientific knowledge is heavily selective, where the framework adhered to by the leading scientists in the field often limits the direction of development [15]. Technological change thus depends on the evolution of a trajectory [16], the so-called "technology trajectory." The technology trajectory develops as the accumulation of learning processes. Giovanni Dosi defines a technological trajectory as the pattern of actualization of a promise contained in a scientific paradigm solving activity (i.e. of "progress") on the ground of a certain technological progress [54]. In other words, technological trajectory is a cluster of possible technological directions whose outer boundaries are defined by the nature of the paradigm itself [54]. Dosi also describes the "technological frontier" the highest level reached thus far upon a technological path with respect to the relevant technological and economic dimensions



[54]. Christensen explains the concept of performance trajectories as the rate at which the performance of a product has improved [17]. The technology trajectory reflects the aggregation of technological advances, following on established technological paths.

However, disruptive (discontinuous) technological innovation is different from technological developments following the technology trajectory. Technological discontinuity results from the resolution of technological rivalries among competitive technologies, as one category of technology substitutes another [18]. A technological breakthrough may disrupt the typical life cycle of a technological advance. In this case, the traditional tools of technology forecasting, such as probability statements are not appropriate for the prediction of discontinuous emerging technology. Discontinuous technological change can be defined as scientific discoveries that break through the usual product/technology capabilities and create an entirely new market [17][18][19]. It is very crucial to forecast disruptive technologies in order to aid a firm's decision making regarding R&D investments and its business plan for commercialization efforts. However, predicting the time at which a disruptive technology will change the existing technology trajectory is difficult. Therefore, given the unique challenges posed by disruptive technology, it is important to distinguish forecasting for "incremental innovation" versus "disruptive innovation", and to distinguish "continuous" technological progress along a trajectory from the "discontinuous" progress associated with the emergence of a new paradigm.



2.3. The Classification of Technology Forecasting Methods

There are multiple ways of classifying technology forecasting methods. Erich Jantsch classified technology forecasting methods in 1967 based on the characteristics of the type of technique used with respect to technology transfer: intuitive, exploratory, normative, and feedback [13]. Stephen Millett and Edward Honton organized TF techniques into three types of analysis: trend analyses, expert judgment, and multi-option analyses [34]. John Vanston assorted technology forecasting techniques based on the type of roles involved in forecasting: extrapolators, pattern analysts, goal analysts, counter-punchers, and intuitors [55]. The TF methods are commonly classified under the headings of "exploratory" versus "normative" [56][57]. Following the lead of the Technology Futures Analysis Methods Working Group, this study divides TF techniques into three categories: normative, exploratory, and a combination of the two [58]. (See Table 2). As Jantsch pointed out, technology forecasting always constitutes an iterative process between exploratory and normative technological forecasting [59].

Exploratory technological forecasting is the attempt to predict the technological state-of-art that will or might be in the future [56]. It starts from today's assured knowledge of what has happened to the present day and predicts future events.

Exploratory methods extrapolate from the past and extend trends through the present and into the future. This form of forecasting is more focused on predicting *how* a new technology will evolve on a predetermined curve (an S-shaped growth curve) as opposed to answering questions about whether technology *should* evolve a certain direction. Exploratory forecasting ascertains what future will inevitably result if trends hold, so that there is little room to affect or alter planning [1].



On the other hand, normative technological forecasting starts with the future and plans backwards. It first assesses future goals, needs, desires, and missions—using some desired future state of events as the starting point—and traces backward to determine the steps necessary to reach the end point and to assess the probability of their success [56]. Planners take into account the dynamic progression of events necessary to accomplish a particular mission, the satisfaction of a need, or state of technological development. Such forecasting mainly focuses on what ought to be or needs to be realized at a certain future time. Normative technology forecasting aims to provide the groundwork to allocate technology-generating resources such as investment, human resources and other assets to reach organizational objectives. The table 2 below summarizes the typical characteristics of exploratory and normative forecasting.

Table 2 The classification of TF methods

Term	Definition	Characteristics	Citation
Exploratory	The attempt to predict	- evolves on a predetermined curve such as S-	[56][58]
	the technological	shaped	
	state-of-art that will	- too naïve	
	or might be in the	- projects anticipated consequences	
	future.	- suggests alternatives to the proposed	
		allocation	
Normative	The statement of what	- more proactive	[56][58]
	ought to be or needs	- too complex and mathematically intricate	
	to be possible at some	- meaningfulness of its treatments of goals is	
	future time	significant	
		- recognition of economic potentials	
		- recognition of responsibility towards society	
		or nation	
		- awareness of constraints (natural resources,	
		company resources, etc.)	
		- recognition of an ultimate technological	
		potential	
		- hedging against threats	
Normative/	Can be used in two		
Exploratory	different approaches	-	



2.4. Exploratory Forecasting Methods

In the early ages of TF, attempts to forecast technological change mostly involved exploratory approaches and Delphi technique [30][60]. Exploratory technology forecasting methods simulate movement in the direction of technology transfer [13]. A description of each technology forecasting method and its practical applications is provided below.

2.4.1. Trend Extrapolation

Trend extrapolation is a widely used technique in technology forecasting. Extrapolation technique makes predictions based on the premise that the future will be a reasonable projection of some type of time-series data, i.e., the old time-series includes all the information needed to predict the future event, and existing trends will continue in the future rather than producing different pattern [30][32]. A number of economic forecasts are based on this assumption.

To apply this technique, forecasters need to collect appropriate data in terms of an attribute or variable over time. Then they can easily predict the future by identifying previous trends and extrapolating them in an intelligent manner. Since this method relies on finding patterns such as trends or cycles in historical data and fitting a relevant curve to the past data, the selection of the appropriate fitting curve is crucial to successful forecasting by extrapolation [61].

There are three types of curve-fitting equations for trend extrapolation based on the rate of technological progress of historical data—linear, exponential, and polynomial techniques [2]. Linear extrapolation is used where a linear growth function is predicted. A polynomial trend equation may be applied to identify the trend where the



trend does not follow either a linear or exponential path. Once forecasters choose the appropriate equation, they can portray the extrapolation mathematically and graphically. Table 3 Types of extrapolation technique

Types	Curve-fitting Equation	Characteristics	Reference
Linear	$Y_{t+1} = y_0 + kt$	- simple and relatively inexpensive - easy to understand	
Polynomial	$Y_{t+1} = y_0 + k_1 t + k_2 t^2$	- inaccurate - appropriate for short-term forecast - not applicable for	[30][32] [34][2] [62]
Exponential	$Y_{t+1} = y_0 e^{kt}$ or $\ln y_{t+1} = \ln y_0 + kt$	discontinuous technology - needs conjunction with complementary methods	

Forecasters have used trend extrapolation to predict technological capabilities, the rate of technological change, the level of product sales, and the length of time it will take to develop a new technology, among many other events, on the basis of available variables and data [34]. This method is closely associated with growth curve fitting and projection. In order to improve forecasting accuracy, trend extrapolation should be employed in conjunction with normative forecasting methods such as cross-impact analysis, expert opinion, and monitoring [63].

2.4.2. Growth Curves; S-curves

Growth curves are the oldest techniques in TF, and widely used in practical applications. Growth curves typically exhibit an "S-shaped" life cycle over a period of years, since experience has demonstrated that technologies tend to evolve in patterns similar to the growth curves of biological systems [64][32]. Forecasters using growth curves also extrapolate futures, based on current and past trends, in a deterministic way.



This technique requires fitting a growth curve to a set of data over time to reflect technological characteristics. A number of growth curves have been developed to predict technological advances. Logistic and Gompertz curves among them are most commonly used methods, having a long history since their inception in the field of demography and later applied to technology forecasting. Growth curves have continuously gained popularity due to their relative simplicity, long history of use in various fields, and the assumption that historical data may provide guidance to projecting a technology trajectory [65].

Growth curves are based on three assumptions [32]:

- The upper limit to the growth curve is known; the upper limit of technological change can be set by natural, fundamental, physical and chemical laws that rule the phenomena used in the technical approach.
- The selected growth curve to be fitted to the past data is correct enough to predict technology trajectory.
- The historical data gives correct coefficients of the chosen growth curves equation; much effort is needed to find representative coefficients based on the historical trend [34].

Growth curves presume that a technology will finally reach its upper limit at a certain time; such curves are employed to forecast how and when a technical will reach its upper limit. It reflects that growth is slow initially until difficulties are overcome, then growth is more rapid until the limit is approached, upon which growth slows down again. Therefore, it is critical to estimate the upper limit using historical analogies. At this juncture, previous experience with a similar technology is key to forecasting



technologies more accurately [34]. Furthermore, growth curves estimate a single variable. If a technology reaches a upper limit, a new technical variable may create a completely new growth curve [32]. These approaches are appropriate for short-term forecasting.

Like life cycle curves, substitution curves are a type of growth curves that project the substitution of one technology for another or the rate of penetration of some technology into a market [66][60]. Since Mansfield, as a pioneer, proposed a technology diffusion model incorporating the rate of imitation and technology adoption, a variety of growth curves such as the Mansfield-Blackman model, the Fisher-Pry model, the Extended Riccati model, the Bass model, etc, have been developed to forecast the S-shaped pattern of technological advance [67]. For the purpose of analysis, the main issue is to determine the curve slope as well as the inflection point using a time series of data. Selecting an appropriate equation of growth curve is somewhat arbitrary. That is why most forecasters experiment with several growth curves to find the best fit to predict the technological change [68].



Table 4 Types of growth curves

Types	Equations	Inception	Reference
Logistic or Pearl	$Y = \frac{L}{1 + ae^{-bt}}$	1923, 1957	[64][69]
Gompertz ³	$Y = Le^{-b-kt}$	1932	[70]
Mansfield- Blackman	$\ln\left(\frac{Y_t}{L - Y_t}\right) = \beta_0 + \beta_0 t$	1961, 1972	[67][65]
BASS	$\ln\left(\frac{Y_t}{L - Y_t}\right) = \beta_0 + \beta_0 t$ $y_t = \frac{\left[1 - e^{-(p+q)t}\right]}{\left[1 + \left(\frac{q}{p}\right)e^{-(p+q)t}\right]}$ $\frac{Y_t}{1 - Y_t} = e^{2a(t - t_0)}$	1969	[71]
Fisher-Pry	$\frac{Y_t}{1 - Y_t} = e^{2a(t - t_0)}$	1971	[66]
Extended Riccati	$\frac{y_{t}}{Y_{t-1}} = \beta_0 + \beta_1 Y_{t-1} + \beta_2 \left(\frac{1}{Y_{t-1}}\right) + \beta_2 \ln(Y_{t-1})$	1976	[72]
Weibull	$\ln\left(\ln\left[\frac{L}{L-Y_{t}}\right]\right) = \beta_{0} + \beta_{1}\ln t$	1980	[73]
NSRL ⁴	$\ln y_t = \beta_0 + \beta_1 \ln(Y_{t-1}) + \beta_2 \ln(L - Y_{t-1})$	1981	[74]
Harvey	$\ln y_t = \beta_0 + \beta_1 t + \beta_2 \ln(Y_{t-1})$	1984	[75]

2.4.3. Bibliometrics; Scientometrics

Literature analysis

There are various definitions for "bibliometrics" or "scientometrics" that numerous researchers have conceptualized. One of the general definitions for "bibliometrics" is "the search for systematic patterns in comprehensive bodies of literature" [76]. Bibliometric techniques were initially employed in the field of library and information science. McKeen J. Cattell, a pioneering psychologist, first used literature data to measure the performance and productivity of scientists in 1906 [77]. There were some bibliometric studies around 1920, using statistical techniques,

⁴ NSRL: Non-Symmetric Responding Logistic



³ Gompertz named after Benjamin Gompertz, an English demographer, who originally proposed the model as a law governing mortality rates in 1825

although using the older terminology "bibliography" [78]. The term "bibliometrics", however, was coined from Pritchard who introduced it in 1969 to replace the term "statistical bibliography" [79]. In this article, Pritchard defines bibliometrics as "the application of mathematical and statistical methods to books and other media of communication." That same year, Vassily V. Nalimov and Z. M. Mulchenko started to use the term "scientometrics", a term of Russian origin that is now mainly used to describe research of all aspects of the literature of science and technology [78]. This term has been widely recognized by the journal Scientometrics, established by Tibor Braun in 1978. Scientometrics involves the sociology of science and science policy, and uses qualitative, quantitative, and computational methods [80]. It appears bibliometrics conceptually includes scientometrics, as it quantitatively analyzes scientific and technological literature. These two techniques have many similarities in the way that they employ mathematical models. Scientometrics and scientific literature analysis also analyzes data based on the publications of researchers, not only to measure R&D activity, impacts, and intellectual linkages as a valid indicator of science and technology [81], but also to identify emerging research fields for forecasting [82][83].

Bibliometrics focuses on statistics with respect to the production, distribution and usage of literatures, rather than the contents of a set of research publications [84]. Bibliometrics aims to analyze the impact of different fields and a set of researchers through exploring historical literature data. In the context of technology forecasting, however, bibliometrics can be defined as the research of statistical analysis to produce and disseminate information concerning the use of recorded literatures for forecasting and decision making. This technique helps to identify the most recent technological



trends and discover hidden patterns within the trend of authors, affiliations, and recent research in the literature.

Bibliometrics is typically classified as in the same category as descriptive research (regarding the characteristics of a type of literature) and behavioral studies (investigating the relationships involving between elements of a type of literature) [76]. Since the Science Citation Index (SCI) was established in 1961, a systematic analysis has been possible and prevalent thanks to the availability of a wealth of data. In addition, the COMPENDEX, COMPuterized Engineering inDEX, was established in 1970 as an Engineering Index (EI) which provides a comprehensive engineering bibliographic database. The rapid evolution of information technology enabled researchers to predict technological advances using such comprehensive databases. Bibliometrics has been popularized and has become more significant in technology forecasting over the years with the advancement of DB system [85][86]. For example, Alan Porter presents an illuminating bibliometric analysis of the methodology trends that helps firms capture emerging technologies [87].

The basic process of bibliometrics proceeds as follows [34]:

- Define the technology area
- Establish the problem domain (year, year of publication)
- Search all scientific and technical publications for relevant articles
- Load relevant data (article title, abstract, author names, references given, country, etc.)
- Analyze the database
- Analyze the implications of indicators



The typical approach of bibliometrics is retrospective, in which one traces the relationship between counts, co-occurrence, and citations among publications to make an evaluation. Since 1927, various types of bibliometric tools have been developed to analyze descriptive statistics, affiliation, authors, countries, and the collaboration of literatures. The major derivatives of bibliometrics are publication counts, citation counts, citation network, co-citation counts, co-word counts, and scientific mapping (cartography). Since D. Price first analyzed literature linkages using citation indices to identify scientific trends, bibliometric citation network analysis has been used to identify research gaps and track emerging research fields in the literature [88][89]. The types of data used in these techniques are as follows:

- Publication count: the counting of scientific publications published by a researcher or a research group
- Bibliographic coupling: one item of reference used by two papers
- Citation analysis: the examination of the frequency, patterns, and graphs of citations in articles and books
- Co-citation analysis: the frequency with which two items of earlier literature are cited together by the later literature
- Co-word analysis: counts and analysis of the co-occurrence of keywords in the publications on a given subject
- Data tomography: an information extraction and analysis system which operates on textual databases, which is keyword-based or index word-based full-text coword analysis



Bibliometrics can help to measure the impact, productivity, R&D activity, and scientific and technological advances of specific areas or authors. Technical reports and scientific papers are appropriate literatures to capture the early stage of technology development [90][61]. High citation is broadly used as an indicator of scientific emergence and the significance of prior cited literatures.



Table 5 Types of bibliometric analysis using literature

Types	Characteristics	Inception	Reference
Citation	- impact factors, number of references, number of citations,	1927 1961(SCI)	[91]
Lotka's law	- $f(n) = k\frac{1}{n^2}$; scientific productivity law (n; number of papers) - a number of papers attributed to specific scientists	1926	[92]
Zipf's law ⁵	 f(n) =k/n; word frequency law the descriptive evaluation of subject authority files and related aspects of indexing 	1932	[93]
Bradford's law	 f(n) = k ln(1+bn); bibliographic scattering law the cumulated total of papers in the first n of the ranked journals are arranged in descending order of productivity, 	1934	[94]
Bibliographic coupling	- meaningful relation to each other, when they have one or more reference in common - based on citation indexing	1962	[95][96]
Citation Network Analysis	- identify scientific structure - identify research gaps and track emerging research fields	1965	[97]
Co-citation	- author connections, subject structure, networks, maps - cluster co-citation - time-consuming and expensive - comparing lists of citing documents in the SCI - more limited internal description of the state of each field	1973	[98]–[100]
Co-word	 evolution and patterns of interactions of different subject areas description of subject area analysis of research trajectory time-consuming and expensive rather more inclusive, contextual, pictures of scientific activity mapping the structure of scientific research interaction dynamics of a research field 	1979	[100]–[103]
Co- classification	- the network of interdisciplinary links between research fields - the co-occurrence of different subject-classification - the strength of interdisciplinary relations - map of the interdisciplinary structure in a single field and whole area - the level of interdisciplinarity in a contributing research field	1987	[104]–[106]

 $^{^{5}}$ If words are ranked according to their frequency of occurrence (f), the n-th ranking word will appear approximately k/n times where k is a constant



Patent analysis

Patent data has valuable information such as the geographical distribution of particular inventions, citation networks, and patterns in terms of particular technology, providing means by which forecasters may monitor technological trends, innovative activities, and new product development [107][108]. Patent trend analysis provides the growth pattern of a technology and helps forecasters predict its life cycle. In addition, patent data may be used not only to generate a time-series of technology trends, but also detect novel technological developments that could represent opportunities or threats to companies.

Such patent analysis has a long history. Patents are public record, and every patent granted since 1836 has been assigned by the Classification Division to its corresponding class and subclass. Using this widely available store of information, Applebaum made the first attempt to analyze patents statistically in the 1920s [109]. Thereafter, a number of studies have used patents to measure innovativeness and difference, a technological advance, and the rate and direction of technology development since the 1930s [110]–[114]. Gilfillan, for example, tracked the inventive cycle of a patent as a technique for technology forecasting in 1935 [115][116]. A forecaster may also use patent statistics such as the cumulative or actual count of patent applications or grants, a time-series of patent trends, and percentage of patents in total as a measure of innovativeness, the rate of technological change, and research output in a sector [117]–[120]. Currently, the advancement of IT (Information Technology)



enables researchers to measure the rate of technological change by actual uses of patent data.

While forecasting techniques using patent data have become more sophisticated, the data necessary for such analysis has become more widely available. The U.S. patent system, the largest patent system in the world, has been fully computerized since 1975 [81]. The U.S. Patent Office founded the U.S. Office of Technology Assessment and Forecast (OTAF) in the mid-1970s. It has provided statistical patent information applied for since 1963 [120]. In 1970, United Nations founded the World Intellectual Property Organization (WIPO) as a specialized agency within its administration, having enacted it in Stockholm in 1967. WIPO then established the International Patent Documentation Center (INPADOC) with the agreement of the Austrian government in 1972, which was integrated with the European Patent Office in 1991. The INPADOC database provides information with respect to patent families as well as patent applications in different countries.

There are many more similarities than discrepancies between literature biliometrics and patent bibliometrics [121]. Patents provide complementary information in bibliometrics. Likewise bibliometrics, patent citations have been typically used as indicators of the importance of an innovation, its technological influence and the diffusion of the technology [122][123]. The citation analysis, however, is somewhat different from literature citation analysis, in that it has two different references: both applicant citations and examiner citations are used to determine novelty, similarity and relevance [124]. Patent citation network analysis has also been used to identify the trajectory of a technological subject and to explore the dynamics of technological



change [125][126]. Patent co-word analysis was first used to improve evaluation of the contents of a large number of patents in biotechnology [127]. Co-word analysis technique provides a research network map which illustrates co-operation, recent technology trends in various sub-fields and promising research directions. In the early 1980s, Battelle devised various patent analysis tools for technology forecasting such as immediacy⁶, patent activity⁷, and patent clustering⁸ [107]. Battelle's process of patent trend analysis involves the following process [34]:

- Define the study objective
- Establish the problem domain (research framework, patent categorization scheme, etc)
- Obtain relevant patents (keyword, patent office classification, citation data, abstract review, full text review)
- Load patent data into software
- Produce computer output
- Interpret analysis results (innovation activity, dominance, company characteristics, portfolio analysis, etc)

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⁶ This method measures the age of the closest prior art in technical and scientific papers or in patents.

⁷ This method considers the number of patents in a given period to find an increasing or decreasing number of firms and inventors coming into a specific area.

⁸ This method looks at how the patents in an area are connected together by citations with a network analysis.

Table 6 Types of patent analysis

Types	Characteristics	Inception	Reference
Citation	- impact factors, number of citations - two kinds of reference citations; applicant citations are occasionally provided by inventor, examiner citations are made more frequently by the patent examiner to warn the applicant of related work - forward/backward citations	1949	[128][124]
Patent citation network	 represents patents and their respective citations as a network uses critical node, core network, and network topological analysis 	1978	[125]
Co-citation	- maps the inter-related development of technical fields - assesses the similarities in their patents	1988	[129][130]
Co-word	 interaction between basic and technological research analysis of research trajectory describes life cycles evolution and patterns of interactions of different subject areas 	1986	[127][131]
Co- classificatio n	- co-classification mapping - belongs to a fixed classification scheme, so might be out of date - simplicity - possible to evaluate the existing classification schemes	1992	[106]

2.4.4. Data Mining; Text (Data) Mining

Through rapid evolution of information technology as well as the flood of available data, Data Mining (DM), Text Mining (TM), Tech Mining, and Database Tomography (DT) have become practical techniques for assisting the forecaster in identifying early signs of technological change [1][84][80]–[82][132][133].

Data mining. In the literature, Michael C. Lovell first used the term "Data Mining" in 1983 to propose econometric data mining in statistical variables' tests [134]. Gregory Piatetsky-Shapiro introduced the concept of Knowledge Discovery and defined it as "the nontrivial extraction of implicit, previously unknown, and potentially useful information from data"[135]. Data mining can be identified as a subset of Knowledge Discovery in Database (KDD), since the KDD process is comprised of data preparation, data selection, data cleaning, data mining, incorporation of appropriate prior knowledge



and proper interpretation of the results [136]. Data mining is identified as a particular element which extracts patterns or models from massive amounts of data with the application of specific computerized algorithms in the KDD process [84][135]. Data mining is defined as extracting useful information and detecting interesting correlation and patterns from any form of data, especially numeric data. Data mining has been theoretically built on the groundwork in database, machine learning, pattern recognition, statistics, artificial intelligence, information retrieval, reasoning with uncertainty, and knowledge acquisition for expert systems [135][137].

Text mining. Data mining typically makes use of a structured database. Textual data mining, however, is concerned with the process of extracting interesting and nontrivial patterns or knowledge from unstructured text documents [138]. On first glance, text mining may appear to be just another type of data mining, since text is just a different form of data. Textual data mining is often considered a much more difficult activity than numeric data mining, however, since it handles textual databases, which are inherently fuzzy and unsymmetrical. Classification and indexing are never completely accurate. Text mining serves as a powerful technique to explore a textual database, discover useful and understandable patterns within them and automatically extract meaningful information from unstructured textual data. Text mining has been used to discover particular patterns in large-scale databases and analyze technological trends. Analyzing the technology performance in a specific field using keywords or phrases can provide an insight for technology forecasting. In recent years, text mining has gained popularity because of its use in exploring the text-based documents such as literature and patents in bibliometrics [139].



Data tomography. Kostoff and his colleagues in the Office of Naval Research developed data tomography, which has a system of algorithms to analyze a large amount of textual data and extract multiword phrase frequency and analyze phrase proximity [85]. Data tomography tool is full-text co-word analysis which can use any key or index word, based upon computational linguistics and lexicography for research evaluation [86]. It assumes the frequencies with which phrases appear in documents are related to the main themes. This method does more than simply retrieve data from any type of large textual databases such as papers, reports, memos, and patents. It also identifies technical thrusts, themes and networks among these areas [140]. This tool has four main processes as follows[139]:

- extract the text to be analyzed from a source of databases
- identify the main themes of the text being analyzed
- determine the quantitative and qualitative relationships among the main themes and sub-themes
- track the evolution of these themes and their relationship over time

One of the most unique characteristic of the data tomography technique is that it includes a phase that utilizes an expert panel to identify the appropriate information in disorganized data as well as to interpret the result [141]. Data tomography has been applied many different fields to identify promising research opportunities and emerging technology areas [139].

Tech mining. In 1993, Alan Porter began to develop and commercialize

VantagePoint in 2000, a software product built upon "Technology Opportunities

Analysis" [87] approach at Georgia Tech. It is a very powerful data mining tool, called



"tech mining" in his papers, for discovering knowledge in search results from patent and literature databases [142]. Tech mining combines text and numerical data to support technology management decision making and technology forecasting [133]. Tech mining, i.e., text mining of science and technology information resources, aims not only to analyze emerging technologies but to provide technology maturity analysis, identify research trends, and create a research network map [143].

Table 7 Data mining tools

Approach	Characteristics	Inception	Reference
Data Mining	- time-consuming - relatively expensive - appropriate for discontinuous technology forecasting	1991	[144]
Data Tomography	- multiword phrase frequency analysis - phrase proximity analysis - time-consuming - identifies promising/emerging research/technology opportunities - develop an independent R&D taxonomy	1991	[85][86]
Text Mining	- time-consuming - relatively expensive - appropriate for discontinuous technology forecasting	1995	[145]
Tech Mining	- not restricted to mining abstract publication and patent records. It combines text and numerical data to best answer the questions	2000	[133]

2.4.5. Analogies; Comparison-Based Prediction

Analogy may be defined as a recognizable similarity or resemblance of form or function, but with no logical connection or equivalence—as distinguished from a model. Forecasting by analogy attempts to predict possible futures by systematic comparison of the technology with a similar one in a certain industry by looking at historical data. Analogizing is a natural process that uses intuition based on similarities and is



commonly used in inductive inference [146][32]. Analogies are a useful method but must be subservient to general guidelines [24]. Thomas O'Connor provides an insightful overview and various applications of analogical techniques in various fields such as mythology, science, economics, politics, military, philosophy, and religion [146].

A prevalent type of forecasting by analogy is the use of growth curves that follow a S-shape to predict the advance of technology [30][147], since many technologies and products follow a pattern where there is a rapid growth stage that faces constraint as the technology reaches saturation level [18]. Martino identified four major challenges with analogies: lack of inherent necessity, historical uniqueness, historically conditioned awareness, and casual analogy [32]. He asserted these problems can be lessened by a systematic method, where the technological change can be measured with regard to several different dimensions (technological, economic, managerial, political, social, cultural, intellectual, religious-ethical, and ecological) to compare two analogous situations. The key success factor of a forecast by analogy is to choose right technologies that are truly analogous to the one being forecast.

Table 8 The characteristics of analogies

Approach	Characteristics	Inception	Reference
Analogies	 easy to use the lack of an integrated set of procedures deterministic intuitive and insightful method only works when relevant historical data is available not applicable for discontinuous technology 	1962	[30][34]



2.4.6. Cross Impact Analysis

Cross impact analysis was first developed for the Kaiser Aluminum Company by T. J. Gordon and O. Helmer at the Rand Corporation in 1966 [148]. Cross impact analysis was initially designed to eliminate some disadvantages of the Delphi method, a group discussion and consensus-building model that too often ignores potential relationship between future events [149][150]. The development of the cross impact analysis technique was the first attempt by forecasters to assess the interaction of technological and social impacts for the purpose of interrelating intuitive forecasts. It does so by taking into account the average probabilities of occurrence for each event and, considering time sequences, since most events and technology developments have some relation with other events and technology developments. This tool provides a useful means for analyzing the relationship between the factors. "Cross impact," coined by Olaf Helmer at the Rand Corporation, refers to this relationship between events and technology developments [148]. It recognizes mutual effects such as the strength, direction and quality of interrelationship between events and technology developments from expert judgments [151]. This method attempts to gather forecasting information systematically for strategic decision making.

There are two major approaches for cross impact analysis [152]. One is the INTERAX (Interactive Cross Impact Simulation) approach developed by S. Enzer at the Center for Futures Research (CFR) in the University of Southern California. The INTERAX approach combines the advantages of trend impact analysis with the strengths of cross impact analysis [153]. This tool involves an analytic model which analyzes evolutionary conditions and physical changes as well as an expert's analysis to



describe social change and policy options in an interactive simulation [154]. The second thing is BASICS (Battelle Scenario Inputs to Corporate Strategies) approach mainly used by the Battelle Columbus Division in 1977. The BASICS tool involves heuristic computations with no foundation in probability theory [155]. This approach is different from INTERAX in that it does not use a Monte Carlo simulation, nor does it involve an independent forecast of the major variables [156].

Table 9 The types of cross impact analysis

Approach	Characteristics	Inception	Reference
	- uses Monte Carlo random basis		[153][34]
INTERAX	- produces path scenario	1966	
INTERAX	- high start-up cost	1900	
	- random selection of initial probabilities		
	- rapid input and editing of data		[157]
BASICS	- long-range perspective	1977	
	- numerous on-line sensitivity analyses	19//	
	- static scenarios		

2.4.7. System Dynamics

The system dynamics method was first introduced by Jay Forrester at MIT in 1961 [158][159]. System dynamics is an analytical approach that analyzes the dynamic behavior of complex social systems to understand and influence how things change over time, based upon traditional management, cybernetic theories or feedback theory and computer simulation [160][161][34]. In 1968, its application expanded from corporate modeling to broader social systems [162]. Since then, system dynamics has been applied to study social, economic and environmental system behaviors and to analyze policies [163].

As currently practiced, the system dynamics technique employs a quantitative simulation approach illustrating qualitative variables extracted from written databases



as well as mental databases built up from experience and observation [63][161][164]. It is a very useful technique in dealing with complex and nonlinear problems that may have side-effects, time delays and a series of interlocking feedback loop structures [158]. Several computer modeling tools and software packages exist to assist in such analysis, such as DYSMAP⁹ (Dynamic System Modelling and Analysis Package) [165], STELLA¹⁰, iThink¹¹, Vensim¹², and Powersim Studio¹³.

System dynamics is used not to predict the emergence of particular technologies, but to forecast future performance and system behavior or a pattern of variation of current system with no modification over a period of time [63]. System dynamics is a completely deterministic modeling that focuses on causal connections, based on the assumption that the system of past development will hold in the future [166]. It requires causal assumptions and the existence of past or analogous data. This method is not quite appropriate as a forecasting tool in that it intends to assume that every event certainly happens, forecasters already know how factors interrelate, and there is only one possible outcome [60][34]. These characteristics do not reflect real-world technological changes. To overcome these disadvantages, system dynamics is often used with other tools to forecast technological change [34]. For example, probabilistic system dynamics integrates system dynamics with stochastic events simulations based on expert decisions [166][167].

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¹³ Powersim studio was developed Powersim Software AS, based in Bergen Norway



⁹ DYSMAP was developed by the System Dynamics Group at Bradford Management Center.

¹⁰ STELLA was introduced by isee systems (formerly High Performance Systems) in the late 1980s.

¹¹ isee systems (formerly High Performance Systems Inc.) in USA developed iThink for business simulation in 1990

¹² Ventana Systems, Inc. created Vensim language and released Vensim in 1988.

There is no integrated set of procedures in system dynamics modeling. Luna-Reyes and Andersen described five different system dynamics modeling processes across the classic literature, varying from three to seven different steps [164]. However, the six-step process of system dynamics proposed by Jay Forrester is as follows [168]:

- Describe the system
- Convert description to level and rate equations
- Simulate the model
- Design alternative policies and structures
- Educate and debate
- Implement changes in policies and structure

The system dynamics model is an iterative process that has dynamic cause-andeffect feedback loops and takes a holistic view. Systems are typically described with a
diagram that shows the links between stated variables, as indicated by arrows. A
diagram can not only illustrate information flow and physical flow but help easily
convey the interrelationship between variables. The arrows represent both the direction
and plus or minus sign of influence between the different factors (positive or negative
effect). The overall sign of the feedback loops is determined by the product of the signs
on their constituent links.

Table 10 The characteristics of system dynamics

Approach	Characteristics	Inception	Reference
System dynamics	 useful in complex and systemic thinking provides clarity and unity the lack of integrated set of procedures real world not always cyclical, having feedback loop deterministic not applicable for discontinuous technology 	1961	[34][164] [169][60]



2.4.8. Agent-Based Modeling

Agent-based modeling (ABM) has been widely used to study multi-level interactions between individual behaviors and social environments in various fields such as economic, biological, ecological, behavioral, demographic, anthropological, cultural, political, technological, and so forth [170][171][172]. ABM has been developed based on the groundwork of Ashby's cybernetics [173], von Neumann's work on self-reproducing automata [174], cognitive science [175], and artificial intelligence [176][177].

Various ABMs have been developed to simulate dynamic heterogeneous agent interaction in given complex social systems as a whole. Typically, there are four different types of network model such as random network, two-dimensional lattice (Cellular Automata), small-world network [178], and Baraba'si and Albert's power-law distribution network [179]. Delre *et al.* proposed a Agent-based simulation (ABS) model incorporating social influences and word-of-mouth processes [180]. They indicated that the speed of the diffusion increased in small-world networks compared to random network.

ABM gives us the benefit of simulation to evaluate this system. In traditional economic theory, basic assumption is that agents interact anonymously with one another via price in the market within a social system. However, in many contexts, agents interact in networks where agents know each other. Bohlmann *et al.* [179] address heterogeneous network using ABM. It aims to understand how social network affects the innovation diffusion process, focusing on interpersonal and intersegment communications within the market.



Due to shortened technology life cycle and higher level of uncertainty, technological changes can be characterized by interactive, nonlinear, and chaotic systems [181]. In the regard, ABM provides a benefit to predict interactive and nonlinear outcomes and phenomena [182]. Hicks and Theis predicted energy efficient lighting options incorporating the rebound effect as well as discontinuous evolution of lighting technologies, using ABM [183]. Kolominsky-Rabas *et al.* also applied ABM to forecast emerging technological innovation of medical devices [184]. On the other hand, Negahban *et al.* used ABM to predict continuous new product development incorporating the future demand forecasting, production management, and volume flexibility [185].

Table 11 The characteristics of ABM

Approach	Characteristics	Inception	Reference
ABM	 bottom-up approach dynamic and heterogeneous analysis useful in systemic thinking, complex and distributed system applicable for discontinuous and continuous technology 	early 1970s	[186][171][172]

2.4.9. Technology Forecasting using Data Envelopment Analysis (TFDEA)

Companies, governments, and other organizations are currently seeking ways to improve their operations [187]. For such entities, Data Envelopment Analysis (DEA) can provide a systematic process for evaluating alternatives, implementing strategies, and improving performance by benchmarking other decision-making units (DMUs). Based on Debreu [188] and Farrell's [189] early work, DEA was developed by Charnes *et al.* in 1978 (CCR) [190] and extended by Banker *et al.* (BCC) in 1984 [191] as a



linear programming procedure for a frontier analysis of inputs and outputs. There are many theoretical and empirical study extensions that have appeared in the literature concerning this analysis. Benchmarking core technology performance and product trends with DEA offers an effective means of determining technological capability over time as well as component development time without the burden of fixed *a priori* weighting schemas. It also provides a clear understanding of key characteristics and assists in forecasting technology trends by benchmarking other companies as fast-followers.

Since its inception in 2001, the technology forecasting using DEA (TFDEA) method can provide an implementable tool to decision makers by bridging the gap between data envelopment analysis (a well-established management science method) and the technology forecasting field. This method measures the technological rate of change in order to forecast future technological advances. There are already some case studies to validate the method applied to a variety of industries including enterprise database systems, microprocessors, hard disk drives, portable flash storage, fighter jets, and turbofan jet engines [192][193][194]. The TFDEA technique provides more accurate results than multiple regression models in cases where both approaches were used.

Table 12 The characteristics of TFDEA

Type	Characteristics	Inception	References
TFDEA	retrospectivequantitative approachapplicable to continuous and some discontinuous technologies	2001	[193]–[195]



2.5. Normative Forecasting Methods

The normative technology forecasting methods screen technology transfer by running against technology movement [13]. The normative forecasting similarly forces forecasters to consider complex social systems that resisted reductionism with its simplified models based upon system analysis [32][196]. The normative approach considers objectives, needs, and future desires as basic elements for forecasts and identifies constraints. A description of each technology forecasting method and its practical applications is provided below.

2.5.1. Relevance Trees

The relevance trees are one of the most traditional normative technology forecasting methods. The concept of relevance trees linked with decision making was first addressed in 1957 by C. W. Churchman *et al.* in their introductory operation research book [197]. Qualitative relevance trees were first designed to aid decision making process [32][197]. The structure of relevance tree is very similar to that of ordinary decision trees. Thereafter, quantitative relevance tree techniques were pioneered by the PATTERN (Planning Assistance Through Technical Evaluation of Relevance Numbers) scheme that was first applied to military and space activity program in large scale by Honeywell's Military and Space Sciences Department in 1963, then refined and extended to all military and space activities in which Honeywell had interest in 1964 [13][198]. Furthermore, this technique was extensively applied to NASA's Apollo Payload Evaluation, US Air Force, and private advertising companies [13].



In essence, the relevance tree technique involves the drawing of hierarchical structure of the technological problems which must be resolved to meet the goals that are at the upper level. The head end of the tree is the final objective of a proposed technology. The hierarchical tree diagrams which have branches and nodes should be deployed by the principle of mutual exclusiveness and collective exhaustiveness [32]. It is prerequisite that forecasters form the hierarchical structure and identify all related factors of technology development. Graphical tree format of relevance trees is very easy to understand various future achievements and relationships among them. Relevance trees can be very useful and powerful tool to identify all problems and solutions and break the performance requirements down for a specific technology in order to achieve some overall objective [32][13]. In addition, the numerical analysis of relevance trees incorporating relevance numbers is a systematic approach to assess probabilities of solutions to meet the objectives of significant social problems [32][52]. The probabilities can be interpreted as the likelihood of achieving the future needs and objectives of individual technology.

Table 13 The characteristics of relevance tree

Type	Characteristics	Inception	References
Relevance Tree	- the hierarchical structure of technology development must be known - applicable for discontinuous/continuous technology - useful for areas of fundamental research - applicable to the guidance of fundamental research contributing to social goals	1957	[32][13]



2.5.2. AHP (Analytic Hierarchy Process); Multi-Criteria Decision Model

The Analytical Hierarchy Process (AHP) is a method that uses criteria and pairwise comparisons between the criteria to ascertain the relative importance with respect to one another. Since Thomas L. Saaty introduced AHP method in 1980 [199], it has widely been accepted as a technique to prioritize the elemental issues in complex problems in decision making process with the various applications of forecasting, selection, evaluation, Benefit-Cost analysis, allocations, planning and development, priority and ranking [200]. With respect to AHP application within academia, AHP has been utilized in manufacturing, environmental managements and agriculture, transportation, power and energy, healthcare, construction industry, R&D, education, e-business, and various other fields.

Although technology forecasting using AHP provides an opportunity containing both the tangible and non-tangible elements, and the capability to develop environmental factors [201], there are a few application literatures discussing the technology forecasting using AHP method. AHP was employed in forecasting the technological capabilities with growth curves [201]. Recently, this technique was applied to a part of the technology roadmapping framework [202].

AHP method analyzes the hierarchical structure of a future technology and measures the relative importance among the classified element technologies affecting the development process of the technology. Weights and inconsistencies are found based upon algebraic methods and are utilized to apply scores to each decision alternative. Thus, the decision alternative with the highest score should be chosen [203]. By comparing the individual pairs of criteria, these models provide an ability to



compare an issue with regards to each immediate higher level. This in turn allows a relative importance to be determined by the decision-maker. A pair-wise comparison, comparing each pair at a time in the corresponding level, is employed to estimate major factors on a numerical scale (1-9).

AHP, however, does have some limitations. The "major issue" with AHP is the accuracy of the weightings leading to the paradigm of being "essentially qualitative and not realistically quantitative [204]." On the other hand, it helps to reach a group consensus in a quantitative manner.

Table 14 The characteristics of AHP

Characteristics	Advantages	Disadvantages	Inception	Reference
 qualitative as well as quantitative subjective judgments evaluation of alternatives applicable for discontinuous/continuo us technology 	- group consensus - easy-to- understand	- accuracy of the weightings - rank reversals are possible - large number of pair-wise comparisons required	Early 1970s	[199][205] [204][206]

2.5.3. Morphological Analysis

J.W. von Goethe (1749-1832) introduced the term of "Morphology" to denote the principles of formation and transformation of organic bodies. This early theoretical morphology was eclipsed by Darwinian evolutionary theory in the late 19th century. Goethe initially provided methodological type-concept in his conception of morphotypes [207]. However, Max Weber simplified, generalized, and popularized typology analysis as a simple concept-structuring method applicable to virtually any area of investigation [208]. Morphological analysis (MA) was coined by Fritz Zwicky, a



Swiss astrophysicist and aerospace scientist, who used the method in 1942, and propagated it via the Society for Morphological Research [209].

The MA analyzes the structure of problems and derive the performance requirements for individual element among the remaining solutions for the normative technology forecasting [32]. MA is concerned with the structure and arrangement of parts of an object, and how these conform to create a whole or a Gestalt [208]. MA is a tool to structure problems rather than solve them [209]. MA can be useful technique to find new relationship or configurations that are not so evident.

The MA has been extended to the areas of policy analysis and future studies. Also, it has been computerized to analyze intricate policy issues, develop future scenarios, and model strategy alternatives [210][211]. In 1995, Tom Ritchey *et al.*, the founder of the Swedish Morphological Society, first developed Casper software, which is advanced computer support for MA at the Institution for Technology Foresight and Assessment under the Swedish Defense Research Agency [210]. Thereafter, they upgraded Casper to a leading proprietary software system, CarmaTM (Computer-Aided Resource for Morphological Analysis), for general morphological analysis in 2005 [211][212].

Table 15 The characteristics of morphological analysis

Type	Characteristics	Inception	Reference
Morphological Analysis	- structures and investigates the total set of relationships contained in multi-dimensional, usually non-quantifiable, problem complexes - qualitative - complementary method for relevance tree - combines with scenario method - applicable for discontinuous/continuous technology - relatively traceable and even reproducible	1942	[32][209] [210][211]



2.5.4. Backcasting

Backcasting is one of the normative technology future analysis techniques which involves setting policy goals at first and then determining how these goals could be reached from desirable future to the present [58]. Backcasting approach can be complementary to technology forecasting tools [213]. Backcasting is not intended to indicate what the future will likely be, based on the probability, but to indicate the relative feasibility and implications of different policy goals and future alternatives on the basis other criteria such as scenario approach [214]. This method, called 'backward-looking analysis' at that time, was first developed by Amory B. Lovins, in the analysis of Japanese electricity supply and demand futures, employing variants of an alternative method in 1974, and then, Robinson introduced first 'backcasting' terminology in 1982 [214]. Historically, this method has the same origin as the strategic and multiple scenario approaches which was popularized by Shell in the early 1970s during the first oil price crisis [215].

Backcasting has been mainly applied in the energy planning field and extended to transportation, governmental programs for sustainable technology development and technology future analysis in Canada, Sweden, UK, and Netherlands [215]–[218]. Backcasting technique adopts a scenario approach in order to identify possible alternatives and to analyze consequences and conditions for the futures to be achieved [219]. Backcasting studies develop images of the future or scenario that attain the goals addressed in the vision. In essence, the backcasting approach involves three major elements [220]: i) defining long term objectives and goals followed by, ii) developing a



short term approach resulting into, iii) the implementation requirements of a research and development agenda. Recently, a participatory backcasting approach has gained more popularity in implementation of this technique [221]. It is very vital to understand the culture, interests, and motives of stakeholders when practicing it.

Table 16 The characteristics of backcasting

Type	Characteristics	Inception	Reference
Backcasting	- better suited for long-term problems - interactive and iterative between future visions and present actions - participatory approach - incorporate discontinuous/continuous technology - explicitly normative and design-oriented	1974	[214][215] [219][221]

2.6. Normative / Explorative Technology Forecasting

2.6.1. Delphi Method

The Delphi method is one of the oldest techniques of eliciting responses and refining expert group decisions [222]. Olaf Helmer, Norman Dalkey, Nicholas Rescher, and others at RAND Corporation, established in 1947 by the US Air Force, developed the Delphi method in the early 1950's, which was designed to remove conference room impediments to a more structured expert consensus [223]. The Delphi technique is to integrate subjective expert opinions with respect to the likelihood of realizing uncertain future technology, the probable development date, desirability, etc. Helmer and Rescher set out the philosophical backdrop for Delphi and set limits of expectation about what can and cannot be known when the questions being addressed fall into the category of "inexact science." [224]. Turoff defined Delphi as "a method for the systematic solicitation and collation of informed judgments on a particular topic" [225]. Different types of Delphi such as policy Delphi [225], decision Delphi [226], and goal-Delphi



[227] have been proposed to meet various purposes. The major series of experiments of Delphi were performed at RAND Corporation to evaluate the procedures [228].

Delphi has gained a large popularity due to its easy implementation and facilitation of group discussions. A variety of technology forecasting and national technology foresight studies mainly use Delphi technique with the participation of hundreds or thousands of experts [27]. It can provide a more feasible forecast in terms of emerging technology and long-range (20-30 years) planning, if trend analysis based on historical quantitative data is not possible. This technique typically is involved when a new technology is emerging, when evaluating ethical or moral considerations, and when expert opinion is the only available source of the prediction of technological change. Moreover, expert opinions are needed when external factors, such as decisions of sponsors and opponents of the technology, and changes in public opinion, are dominant [32].

The Delphi process has two distinct forms: conventional Delphi and Delphi Conference [223]. Delphi process consists of preparation, consecutive survey with 2-6 iterations until a general consensus of the outcome is reached, analysis and implementation. It provides the results of each round so that experts may change their previous assessments to same questions. This method fundamentally relies on the quality of expert panels' knowledge, experience, and judgments. The size of an expert panel in Delphi basically depends on the number of issues. A large number of respondents appear to perform better in order to adequately treat some issues, but the groups with seven or eleven participants are more effective in forecasting than larger groups according to Brockhoff's experiments of Delphi performance [223]. Delphi



process gives the participants objective feedback from structured group consensus. The basic procedure of Delphi methods proceeds as follows [228][34][32][229]:

- Identify goals of the study and requirements
- Structure the questionnaire with scale or open-ended answer to support study goals
- Identify the experts in each field
- Anonymous response
- Iteration (2-6 times, 3 or 4 as usual)
- Controlled feedback
- Statistical group response (κ²test, median and upper and lower quartiles for review)
- Present the consensus forecast

It is critical to carefully control a series of intensive questionnaires and feedback between rounds. Panel opinion is accepted as a relevant aggregate of individual estimates on the final round.

Table 17 The characteristics of Delphi

Characteristics	Advantages	Disadvantages	Inception	Reference
- exhibit bipolar views	- the possible	- time		
not forcing consensus	participation of	consuming		
- foster the better use of	diverse experts	- biases of expert		
group interaction	in disparate	decisions		[27][32]
- qualitative approach	geographical	- forced	early	[34][223]
- subjective, intuitive,	areas	consensus	1950's	[228][230]
anonymous	- structured	- little control		[231]
- indirect interaction	group	over participants		
- iteration and	consensus			
controlled feedback				



2.6.2. Nominal Group Technique (NGT)

The nominal group technique (NGT) was introduced in 1968 by Delbecq, Van de Ven, and Gustafson as an organizational planning tool [232]. The nominal group is illustrated as a group in which each panel expert works in the presence of others but does not verbally interact [233]. There is no preliminary discussion in NGT. NGT is designed to remove the problems of group interactions. NGT is similar to Delphi method in that it uses expert panels. In contrast, NGT effectively holds structured meetings facilitated by a third party moderator, and involves efficient discussions among participants concerning each expert's initial opinion [52]. NGT is a very efficiently structured process for idea generation and group consensus in terms of assessing particular issues [234]. NGT prevents a bandwagon effect on the majority such that the group leader or the strong expert may affect the panel consensus by prioritization using secret ballots during the discussion of voting phase. Hence, it is of vital significance to carefully select experts in order to remove this disadvantage in the NGT. There are two types of group idea generation process in NGT: 1) an intraorganizational group decision making, and 2) a solicitation experts' or citizens' views as input for public policy formulation [235].

The NGT has been used for participatory problem solving approach by group analytical decision making in the social science field [233] and extended its application to almost any problem and field, such as health care studies [236][237][238], social services [239], consumer research [235], new product development [240], and information system [241]. The final output in the NGT is a rank-ordered list of new ideas assessed by expert panels with the number of points which account for the level of



consensus. The 6-step process of group idea generation and prioritization in the NGT are as follows:

- Introduction of the task statement
- Individual, silent generation of ideas
- Round robin listing of ideas
- Clarification of ideas
- Consolidation of ideas
- Voting and ranking of ideas by secret ballot

Table 18 The characteristics of Nominal Group Technique

Characteristics	Advantages	Disadvantages	Inception	Reference
- qualitative approach - alternative to Delphi method - information shared - involve intensive discussion - aims at panel consensus - applicable to wide variety of areas	- participation of all members - minimizes group "noise" - structures and collects many creative ideas - easy to learn - easy to integrate into programs and projects of larger scope - intra- and intergroup comparisons are possible	- mechanical or overly simplified - structure does not allow for interaction of ideas	1968	[232][234] [235][52] [34]

2.6.3. Scenario Planning/Writing

Scenario planning has gained its popularity in technology forecasting methods and decision making in the face of uncertainty. It formally started from the use of computer simulation to measure the probabilities of the atmosphere and planet catching fire in the Manhattan project in 1942 [242]. RAND Corporation also introduced scenario planning for the US military purpose by Herman Kahn in 1950s, based on the



previous groundwork of computer simulation, game theory, and war games [243]. Furthermore, private companies such as Royal Dutch/Shell and GE developed scenario planning technique for a corporate strategic planning in the late 1960 and early 1970s [34][244][152]. For instance, Shell's adequate and timely reaction to the oil crisis in 1973, drew attention to the scenario analysis [244][245].

Kahn and Wiener, the pioneers in scenario planning, first defined scenario as "hypothetical sequence of events constructed for the purpose of focusing attention on causal processes and decision-points" [246]. Scenario can be simply considered as a series of events that an expert imagines the plausible future occurrence. Schoemaker illustrated scenario planning as "a disciplined method for imagining possible futures in which organizational decisions may be played out" [247]. Scenario planning is the use of internally consistent narrative descriptions of particular sets of events, diversely possible situations or developments in the future. It explores the future to identify multiple outcomes that can occur. In essence, scenario planning is a systemic approach to create alternative and dynamic stories about many plausible futures in complex and uncertain business environments rather than to focus on a possible single outcome [248]. It explores the joint impact and implications of various different ends. This technique is useful in drastically changing environments including disruptive technologies.

Scenario planning can be variously classified based on the different aspects such as project topic, process design, time, etc [249][250]. There are, however, two forms of distinct scenario approaches with respect to technology forecasting: projective (descriptive) and prospective (normative, prescriptive) [216][249][251]. Projective scenarios explore possible future images projected from current situations to the future



forward. On the contrary, prospective scenarios describe probable or preferable futures on the basis of different visions of the future. They write scenarios how to reach several significant objectives, which is similar to backcasting tool.

The theoretical foundations of scenario planning are relatively fragile [248][252]. In practice, however, there has been a variety of applications of scenario planning in diverse fields such as energy, electronics, aircraft, telecommunication, healthcare, and environment industry [250][253][254][255]. In the real business world, three distinctive forms of scenario planning have actively been implemented [153]. In this section, the main focus has only been on the "Intuitive Logics" tool typically introduced by Pierre Wack, a planner at Shell Française [244][245], because the other two approaches trend impact analysis and cross impact analysis—are described in detail in the other sections. The "Intuitive Logics" was mainly used by SRI International, Global Business Network, and Shell [153]. The Intuitive Logic approach considers a complex set of relationships to make a better decision among STEEP headings (social, technological, economic, environmental, and political) factors that are external environments to organization [153]. This method involves a series of intuitive logics generated by expert communication and analysis without depending on the complex computer simulation model [156]. This approach strongly depends on the participants' intuition and the communication skills of the expert panels [250].



Table 19 The summary of three approaches of scenario planning

Types	Characteristics	Inception	Reference
Intuitive Logics	 developed by Shell appropriate for short-term forecast restricts the diversity of the constructed scenarios 	late 1960s	[245][153]
Trend Impact Analysis	employed by the Future Groupa combination of statistical extrapolationswith probabilities	early 1970s	[153]
Cross- Impact Analysis	- practiced by Battelle with BASICS (Batelle Scenario Inputs to Corporate Strategies) and the center for Futures Research (INTERAX) - a highly formalized method	1966	[34][153]

Scenario developers must be experts in all aspects of the proposed technology to seek out better decisions. They answer two types of questions: 1) 'precisely how might some hypothetical situation come about, step-by-step?' and 2) 'what alternatives exist, for each actor, at each step, for preventing, diverting, or facilitating the process?' [32].

The basic procedures of scenario writing are as follows [256][153]:

- Identifying the decisions and strategic concerns
- Analyzing major appropriate factors (internal and external environmental forces; social, technological, economic, political, and competition)
- Elaborating the assumptions to be implicit in the scenario logics with its scope
- Identifying related sources of information for major factors
- Analyzing the issues/points of divergence resulting from conflicting factors in the current situation
- Consolidating the information and predictions obtained to develop internally coherent pictures or development pathway



Analyzing implications for decisions and strategies

Table 20 The characteristics of scenario planning

Characteristics	Advantages	Disadvantages	Inception	Reference
- manpower intensive - embraces qualitative perspectives, quantitative data, and macroscopic factors - tends to be broad and conceptual rather than specific	- very flexible - incorporates discontinuous technology or disruptive events	- can be too qualitative - relatively expensive - time- consuming	1950s	[243][34] [250][257]

2.6.4. Trend Impact Analysis

The trend impact analysis was incepted in the early 1970s, diversified from the scenario planning tool [258]. This method was mainly used to add quantification to a scenario by The Futures Group consulting firm. It is primarily a descriptive approach evolved from the traditional forecasting tools, on the basis of extrapolating historical data with no consideration of unprecedented future situations [152]. This tool aims to enhance the accuracy and usability of approaches to trend extrapolation. The trend impact analysis not only collects past data and projects this to generate 'surprise-free' future trends, but also employs expert judgment tool to seek the possibility of occurrence and its future impact regarding unprecedented events [259]. This technique, in other words, provides a systematic means for combining both statistical extrapolations and expert judgments to identify a set of future situations. The critical part of this tool is to estimate the magnitude of impact at each extraordinary event on the trend from experts' decisions such as the largest impact or the steady-state impact and the beginning time of unusual trend [259]. It captures the product of probabilities



and impacts in selected significant situations which the forecasters can focus on in an efficient manner.

When compared to the cross-impact analysis, the trend impact analysis merely renders an independent forecast of the key dependent variable, with no consideration of evaluation of possible combination of each event [153]. It also needs to utilize the cross-impact technique to calculate the probability of impacts of coupled events [259]. Furthermore, this technique requires a long past data for extrapolating trends. For these reasons, it is not a popular method among forecasters. The trend impact analysis consists of typical five steps as follows [156]:

- Collecting time-series past data
- Generating a surprise-free extrapolation
- Establishing probabilities of events occurring over time
- Adjusting extrapolation
- Writing scenarios from at least two of the forecasts

Table 21 The characteristics of trend impact analysis

Type	Characteristics Inc		Reference
	- relatively simple and easy to use		[258][259] [152]
	- requires long historical data for time-series		
Trend	analysis or causal methods	early	
impact	- ensures internal consistency	1970s	
analysis	- provides probable range of possible situations	19708	
	- well suited for policy evaluation		
	- partially applicable to disruptive technology		

2.6.5. Technology Roadmapping

Technology roadmapping was first used by Corning and Motorola to develop corporate and business strategy in the late 1970s [260]. In 1984, Motorola first



introduced its own product technology roadmap as a planning tool to better position themselves and their product in the market. Motorola's product technology roadmap aided the communication between design & development engineers and the marketing personnel, in order to forecast technologies which would be required in future products [261]. Motorola popularized its own technology roadmap which had a single layer roadmap, focusing on the technological evolution associated with a product and its features as a business planning tool in 1987 [262]. The technology roadmap is a useful tool for managing R&D planning as well as identifying the future of technological progress. Robert Galvin, former Motorola chairman, defines technology roadmap as "an extended look at the future of a chosen field of inquiry composed from the collective knowledge and imagination of the brightest drivers of change in that field" [263].

Technology roadmap is mainly developed for three purposes: technology forecasting, planning, and communication. Technology roadmapping, in other words, attempts to reveal a specific characteristic or an attribute of technology development over designated future time. It is also an effective tool for technology planning and communication which fits within a broader set of business planning [264][265]. Finally, this method provides a useful means for the communication within cross functional organization. Technology roadmapping technique has gained significant and subsequent acceptance within corporations[266][267][262][268], government agencies [269]–[272], and national foresights [273].

Technology Roadmapping takes a retrospective (top-down) approach which backwardly illustrates how to accomplish a given target from decades past to the present, or a prospective (bottom up) approach which looks forward from the present to



the future, or a combination of the two [274]. Most technology roadmaps, however, involve a prospective process which has two distinctive types of analysis: market pull and technology push [275][274]. The prospective approach is typically employed in technology forecasting. In addition, there is no standardized roadmapping process to generate roadmaps [276]. It differs based upon the business objectives, product and service types, available resources, and knowledge and information, etc [277].

There are three major questions consider when developing technology roadmap [278]:

- Where does a company want to go?
- Where is a company at now?
- How can a company reach its target?

Table 22 The characteristics of technology roadmapping

Type	Characteristics	Inception	Reference
Technology Roadmapping	 relatively expensive exploratory / normative forecasting tool subjective exercise not much applicable to disruptive technology but there are some attempts combining with other techniques 	late 1970s	[279][260] [262][280] [281]

2.7. Analysis of the Relationship among TF Methods

This study attempts to analyze the historical relationship between normative and exploratory methods in the literature and identify the methodological linkages among them. Some technology forecasting methods are employed together to predict technological changes or innovations, but others are not. It is, however, theoretically inappropriate to use composite methods among them in order to solve practical



forecasting problems, owing to conflicts of assumptions. Furthermore, the selection of proper technology forecasting methods depends on the nature of the technologies [26]. Therefore experience and expertise in various TF techniques is important in selecting the appropriate forecasting models. This study categorizes technology forecasting techniques according to exploratory and normative approaches. This study analyzes the applicability of technology characteristics such as disruptive/discontinuous and continuous technology. Figure 2 presents a matrix of TF methods by type of techniques and technological characteristics. Within each cell, TF methods are listed in descending order of frequent and effective uses.

Discontinuous	Data Mining(Text Mining) Bibliometrics (literature, patent, etc) Agent-based modeling Cross Impact Analysis	Delphi Scenario Planning Nominal Group Technique Trend Impact Analysis	Backcasting AHP Relevance Trees Morphological Analysis
Continuous	Growth Curves System Dynamics Trend Extrapolation Analogies Agent-based modeling TFDEA	Technology Roadmap Trend Impact Analysis Delphi Scenario Planning Nominal Group Technique	Morphological Analysis AHP Relevance Trees Backcasting
	Exploratory	Exploratory/Normative	e Normative

Figure 2 A matrix of TF tools

There are a number of articles that combine multiple TF tools in order to offset the weaknesses of one forecasting technique, such as technology roadmapping with scenario technique [282], Delphi with cross impact analysis [283], bibliometric with



growth curves and system dynamics [23], and technology roadmapping with morphological analysis and text mining [284], and so forth. This study identifies research method linkages for technology forecasting through a review of the literature. Figure 3 illustrates the correlation among TF methods. Some articles combine the exploratory and the normative approaches to TF. Most of linkages are connected between exploratory and exploratory/normative methods or normative and exploratory/normative techniques. Furthermore, there are a few direct linkages between normative and exploratory methods, excepting the combination of text mining and morphological analysis. These relationships among TF methods reflect similarities in assumptions as well as methodological backgrounds among them. Additionally, a research gap can be found in the correlation map among TF techniques.

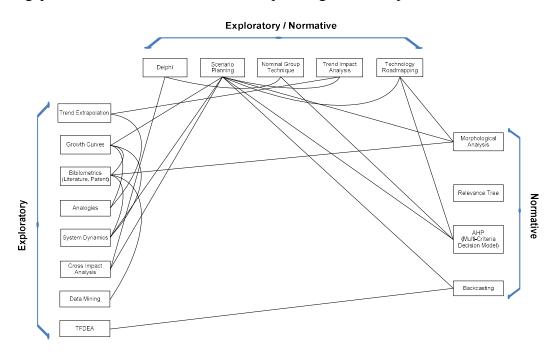


Figure 3 The connection map among TF techniques



2.8. Measuring R&D Performance

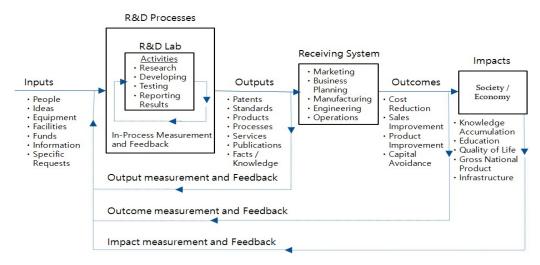
Firms have been focusing on the effectiveness of their R&D investment as well as uses of R&D. An effective R&D operation is considered a primary enabler of competitive advantage in today's drastically changing business environment [10][285]. Since R&D is a creative, unique, and consists of unstructured process, it is difficult to evaluate its performance. Certain elements inherent in R&D such as time lag, joint costs and returns, and imputation of a given cost or return item to a given project or program cause trouble in measuring its performance [286][287]. Unfortunately, there are still no methods that are widely accepted for measuring the causes and effects of inventive activity [288][289][290]. In times of economic downturn, the evaluation of performance in a firm is needed to justify R&D investments. Furthermore, the accountability and effectiveness of R&D program are highly emphasized. Measuring R&D performance has been developed in response to the needs of various organizations by employing different methodologies. The literature regarding R&D performance focuses on three forms of contributions such as improvements in the capabilities and quality of existing products and processes, new product or process developments, and advances in knowledge for future improvements in products or processes [291].

Various forms of R&D performance present difficulties in determining which elements to measure [292]. A variety of outputs, outcomes, and impacts of R&D are illustrated in Figure 4. Output is the instant and direct result of the R&D. Outcome is the expected result that will be realized through receiving system based on the output [293]. Impact is the long-term effect of the R&D on the society and economy [294][295].



There is no single approach or method that provides an entirely satisfactory evaluation. To this, there is no question on that it is difficult to compare such subjective data to quantitative indexes. In this research, therefore, the measurement of R&D performance focuses on output indicators rather than outcomes or social impact indicators, because the former is not only countable and can be measured at any given time, but also replicable based on verifiable sources.

Rubenstein and Geisler suggested that indexes measuring R&D performance should be defined on the basis of the information-gathering system. In this regard, typical output indicators are patents, new products, new processes, publications, or simply facts, principles, or knowledge that were unknown before [296]. R&D performance can, however, be measured by various variables depending on the focus of the analysis. This study focuses on evaluating the technological performance of R&D efforts of a firm. In addition, the study reviews the literature to seek an objective measurement of R&D effectiveness.



source: modified and adapted from [293][286][297][298]

Figure 4 The R&D performance as a system



2.8.1. Patents

Technical performance can be used to measure R&D. Technological inventions and innovations have been playing a crucial role for a firm to compete in the market. Patents can be considered as the output of technically successful R&D activities. Several studies indicate a positive relationship between patents and R&D investment in U.S corporations depending on industry sector [299][300][301]. Jaffe indicated that patent counts and R&D tend to be correlated without a time lag [302]. However, other studies still show little correlation between the level of R&D spending and financial success [303]. Consequently, it is not enough to suggest that spending more on R&D is always better [304].

The more R&D intensive firms have a greater tendency to patent [305]. Comanor and Scherer suggested that the number of patents is highly correlated with the number of research personnel [306]. There have been discussions in the literature as to whether patents are simply an indicator of R&D expenditure, or whether they measure the output of invention. Several studies indicated that patents have a strong association with ratings of basic research excellence [307][308][309]. On the other hand, there has been mixed support for the association between patents and patent citations [310].

Mansfield indicated that the propensity to patent has inter-industry and inter-firm difference, and difference over time [311][312], and the quality of patents varies enormously. Not all inventions or innovations are patented. The percentage of innovations patented is limited to maintain secrecy among other reasons [313]. Even given all these limitations, patents have a compelling advantage providing a wealth of qualitative and quantitative information on technological change [299].



Patents of a proprietary nature have been used for identifying invention, innovations, and innovativeness in a number of studies [312][313][314], despite the fact that they, as intermediate elements, are not a direct measure of their commercialization potential [315]. Patents can be regarded as a medium to reflect the firm's intention to commercialize an innovative idea or invention. There have been a variety of indexes to measure R&D performance by patents such as total number of patents filed or granted, and total number of patent citations. The most common output indicator is a patent such as number of patents granted or filed. For the virtue of easy accessibility via objective databases, this study selects the total number of patents as an output variable to examine the relationship between technology forecasting, technology planning activity, R&D performance, and business performance.

2.8.2. Products

Product innovations are outputs or services that are introduced for the benefit of customers or clients [316]. Product innovations have a market focus and are primarily customer driven [316]. To gain or maintain competitive advantage, a firm has to innovate in new products or services. The sustainable and profitable growth comes from new or improved products, new services, new or improved processes, or new business model. Francis indicated that corporate R&D should focus upstream and final product engineering [317]. A firm needs to keep growing its technological capability to protect its position [318]. The concept of new products should be determined to measure R&D performance since they can be defined in various ways based on a firm's strategy and competitive environment [319].



Several studies of successful technological innovations indicate that they are most frequently applied to new products rather than processes [320]. Kleinschmidt and Cooper examined the association product innovativeness and profits at the product level [321]. Many studies use 'the number of new products released to the market' as a common quantitative index to measure R&D outputs [289][286][297][287][317].

2.8.3. Processes

Process innovation can be defined as "new elements introduced into an organization's production or service operations in order to produce a product or provide a service" [322][323][324]. Process innovations have an internal focus and are primarily efficiency driven [316]. R&D efforts should be directed toward enabling manufacturing processes that use new and different technology [317]. Process innovation is the central type of research in producing rapid effects on corporate profits [325]. Davenport differentiated process innovation from process improvement, which seeks a lower level of change [326]. To measure the entire list of process contributions from R&D is relatively complex [287].

Geisler suggested improved performance of processes, processes used by others, and number of processes transferred to users or clients as intermediate R&D outputs [297]. Galloway also indicated the critical contribution of R&D resources for process improvement or the elaboration of an established product line for evaluating R&D [287]. Gold pointed out the three types of contributions from R&D with respect to process: improvements in the capability and quality of existing processes, development of new processes yielding major commercial advantages over competitors, and advances in knowledge likely to generate future improvements in processes [291].



2.8.4. Cost Reduction

R&D tends to be applied to existing product extensions and to process refinements as competitors try to reduce their production costs [316]. Cost reduction in existing products contributes to competitive performance. Patterson pointed out that technical innovations may reduce the cost of existing operations [327]. Although cost reduction seems to be the evident benefit for major R&D accomplishments, short-term cost reduction and short-term sales are often considered to be less significant for overall growth [328].

Geisler proposed new indicators for R&D performance including changes in the cost of products in manufacturing and actual cost reduction in user's performance/processes by considering the clients and the impactees [297].

2.8.5. Standards

For polymer science and standards, Rubenstein and Geisler suggested a number of new or improved standards as an immediate output from federal laboratory science and technology programs [286]. This article emphasized that managers or researchers must develop the R&D performance index suited for their own organizational settings.

2.8.6. Professional Recognition

Professional recognition includes public speeches, prizes, honors, awards, press and media coverage, reviewing and publishing articles and books, and serving on professional society and governmental committees.

When an organization emphasizes basic and applied research over development engineering, Francis suggested professional recognition or technical accomplishments for measuring R&D effectiveness [317].



2.8.7. Technology Transfer

Autio and Laamanen defined technology transfer as the "intentional and goaloriented interaction between two or more social entities, during which the pool of
technological knowledge remains stable or increases through transfer of one or more
components of technology" [329]. Technology transfer is a typical form of research
transformation and the result of technology diffusion activities. Technology transfer is
distinct and may be readily identified. Azzone and Maccarrone introduced the indices of
tacit technology transfer in a informal form [330].

For the output indicator of R&D effectiveness, Geisler suggested a number of outputs transferred to users or clients (e.g. products, ideas, improvements, etc) [297]. Autio and Laamanen addressed three types of output indicators of technology transfer: research and technology outputs, commercial outputs, and monetary and resource outputs [329]. This output indicator includes economic sense in that the firm's net income can be generated from royalties.

2.8.8. Publications

Publications are a common means by which technical knowledge circulates.

Scientific publications may lead to technological innovations, which are the catalyst for new product or process development [307]. The number of elite scientists in a firm is more highly correlated with publications rather than patents [331]. Resource intensive industries have more propensity to publish papers rather than patents when compared with capital intensive industries [331].

The number of publications is widely used to assess both a university's performance and an individual scientist's performance, as well as to measure scientific



and technical outputs [297][332][333]. Narin *et al.* [307] suggested that papers can be a valuable indicator for the pharmaceutical industry. Gambardella used the number of scientific publications as a proxy for the R&D capabilities of a firm [334]. To overcome the limitation of the number of publications, Sher and Garfield examined the number and variety of citing publications for evaluating the work of individuals and organizations with a qualitative perspective [335].

2.8.9. Facts/Knowledge

Facts and knowledge include the number of technologies and practices formally transferred into operating units, number of requests of consulting on projects, participation in design review, and improved capability of user to absorb/utilize technical knowledge [317][297]. This indicator is also one of the technically driven criteria. There is little research on this index to assess output from R&D performance. The availability of such information may cause difficulty in adopting this indicator for R&D measurement.



Table 23 The summary of output indicators from the literature

Output	Output Description Defendance			
Element	Index	Description	References	
Patent	Patents	Total number of patents are filed or granted in a certain period of time	[286][297][312][336][119] [337][317][120][338][306] [339][340][302][334][288]	
	Patent filed	Total number of patents filed in a certain period of time	[341][300]	
	Patent granted	Total number of patents granted in a certain period of time	[311][305][331][112][307] [342]–[347]	
	Number of patent citations	Total number of patent being cited	[297][336][348][344][346] [123][307][333]	
	Number of patent ratio	Number of patents per total number of R&D employees	[349]	
	Number of innovations based on patents	Total number of innovations based on patents	[314][336]	
Products	Number of new products	Total number of new products that are released to the market by a firm	[286][297][289][287][317]	
Processes	Number of improved or new processes	Total number of improved or new processes	[297][286][287]	
Cost reduction	Actual cost reduction	Actual cost reduction/savings in client/user's performance	[297][327][328]	
Standards	Number of new or improved standards	Total number of new or improved standards	[286]	
Professional Recognition	Awards and Honors	Total number of awards and honors by a firm	[317][297]	
	Number of technology transfer	The overall transfer of outputs to external organizations	[297][329]	
- ·	Licensing	Total licensing income	[346][329]	
Technology Transfer	Number of new jobs	Total number of new jobs created by the spin-offs	[329]	
	Amounts of venture capital investment	Total number and amounts of venture capital investments in the spin-offs	[329]	
Publications	Number of publications such as articles, reports, books	Total number of publications by a firm	[334][317][331][332][307]	
	Number of requests of reports	Total number of request of reports by elsewhere in the company and from outside	[317][297]	
	Number of publication citations	Total number of publication being cited	[335][297][333]	
Facts/ Knowledge	Number of technologies and practices	Total number of technologies and practices transferred into operating units	[317]	
	Number of requests of consulting	Total number of requests of consulting on projects, participation in design review	[317]	
	Information and its use by others	Improved capability of user to absorb/utilize technical knowledge	[297]	



2.9. Measuring Business Performance

Economist and strategic management researchers have paid attention to firm performance over a century. In the earlier studies, Joseph Schumpeter created the theoretical concepts and tools in the most famous book titled "The Theory of Economic Development." He explored the evolution of economic development. This Schumpeterian effort formulated a remarkable notion of economic development. The firm equipped with R&D division became the central innovative actors in Schumpeter's theory [350]. In the history of the neoclassical theory of the firm, neoclassical theorists try to look inside the black box of the firm. Economists treat technology as an exogenous or endogenous variable in the aggregate production function in order to investigate the economic growth [351][352][353]. A great deal of theoretical and empirical research has been made on productivity growth and measured technical change at the levels of single industries and whole economies.

Penrose, meanwhile, pioneered the foundation of resource based theory, and regarded firm growth as a dynamic process of management interacting with resources [354]. She applies this concept to the growth of the firm and its diversification. The resource based theory focuses on the heterogeneity of firm's a set of capabilities and performance. Strategic management, strategy, and firm differences are at the junction of its inquiry. Strategy formulation focuses on organizational resources and competencies aligned with environmental opportunities [355]. Teece explored efficiency rationale of firm diversification by incorporating economies of scope and transaction cost economics [356][357]. Wernerfelt advanced resource-based perspectives on both competitive advantage and firm growth [318]. He proposed a new focus on technology



in strategy. Barney pointed out that firms can attempt to develop better expectations about the future value of strategic resources by investigating their competitive environments or by analyzing the skills and capabilities they already control [358]. He indicated that strategic choices must come from the analysis of competitive advantages based on strategic resources rather than a competitive environment. Nelson addressed inter-firm differentials with respect to strategy, structure, and core capabilities [350]. He touched upon the emerging theory of dynamic firm capabilities. However, Teece and Pisano triggered a flood of discussion on the theory of dynamic capabilities in their earlier studies [359][360]. They defined dynamic capabilities as an idiosyncratic set of learned processes and activities that enable a firm to generate a particular outcome.

In the line of this context, Prahalad and Hamel introduced the concept of core competence of a firm, which is difficult for competitors to imitate as embedded skills, the engine for new business development, and the collective learning in the organizations [361]. They defined core competence as a bundle of skills and technologies. A core competence is not only enhanced over time as they are applied, but also provides potential access to a wide variety of markets. They suggested that a firm should develop a corporate-wide strategic architecture for acquiring and deploying core competencies. They also emphasized the needs of 10 to 15 year long-term planning for developing a map of core competencies to bridge the gap between emerging customer needs and changing technologies. These approaches understand the firm performance as a result of the efficient use of unique company capabilities. Furthermore, they emphasize the sensing like technology forecasting and planning setting.



Mitchell suggested a single system for the strategic management of technology in planning frameworks, which helps firms to deal with the issues of technological change, and their impact on strategy [328]. Cooper indicated that firms' strategies reveal the nature of technology employed [362]. On the flip side, emerging technology may lead to new businesses and even cause a significant change in corporate strategy [363]. For firms in research-intensive industries, technology innovation matters to drive their growth and competitiveness. Strategy is one of the major determinants of business performance. R&D is a cornerstone of an effective innovation strategy [364]. A firm must deploy R&D investments more strategically as well as effectively. Technology-focused firms take into account technology as their primary asset in business strategy. R&D must be connected with a firm's overall business strategy [285]. The business strategy is coupled with technology strategy. Technology strategy needs to be a subset of the strategic plan [365].

Planning is an integral part of strategy formulation [366]. One of significant contributing factors to corporate success is a formal planning system [366]. Drucker indicated that planning should be an integral part of a well-managed company [367]. Several studies have been conducted to measure the financial impact of strategic planning. Thune and House showed the strong relationship between formal planning and financial performance for firms in six industries [368]. Karger and Malik also found a positive relationship between formal integrated long-range planning and economic performance involving capital spending, stock price, and distribution of earnings for seven industries [369]. Wood and LaForge indicated a strong association between comprehensive long range planning and subsequent financial performance for a bank



industry [370]. Meanwhile, Kudla indicated no relationship between formal planning and financial performance [371]. Based on the comparative analysis, Armstrong found formal planners were superior in ten cases and concluded planning seemed most useful in situations involving large changes [372]. Although research on the relationship between planning and performance has yielded inconsistent results [373][4], a meta-analysis of 26 studies allows valuable insights by indicating that strategic planning has a positive relationship with firm performance [374]. In recent study, based on meta-analysis of 46 studies, Brinckmann *et al.* also found a positive association between business planning and performance in small firms [375].

The technology planning and corporate strategic planning processes must complement each other in order to manage R&D both purposefully and strategically [376]. Fusfeld emphasized that a firm must learn to integrate technology management with strategic planning [376]. In general, firms continuously keep managing and planning their strategies accustomed to drastically changing environment. Zahra and Covin investigated the relationships among business strategy, technology policy, and firm performance [377]. Zahra examined the association between technology strategy and financial performance with considering moderating effect of the environment on them [378].

Franko examined the R&D factor in world-wide corporate performance and tested the association between corporate R&D intensity and sales growth and world market share [379]. He stressed the crucial role of technology in the growth of the individual industrial firms. Mendigorri *et al.* demonstrated that four factors such as firm's R&D activities, integration of the R&D activities with business strategy, R&D planning,



cross-functional integration influence on the R&D effectiveness [380]. They also provided the evidence of positive relationship between R&D effectiveness and the firm's financial performance.

Leonard indicated causal influence of R&D intensity on the rate of sales growth [381]. Profit and R&D have a recursive relationship and influence one another [311]. The important question is how to capture expected returns from R&D. Illustrated in Figure 5 are all these arguments and associations among TF, information system, technology planning, business planning, technology strategy, business strategy, R&D performance, business performance, and financial system as described above.



Figure 5 Overview of technology to business management

A number of outcome indicators are identified from the literature. Scholars and practitioners have been using partly different indicators to measure business performance [382]. In this research, the measurement of business performance is based on outcome indicators rather than outputs or impact indicators, because that data convey economic sense. For example, the more patents lead to subsequent change in business



performance such as sales growth, or profit increases [383][342]. The new invention should lead eventually to the generation of financial profit. There is no significant trend favoring a single measure of firm performance. Due to cost-effectiveness as well as no viable alternative, many studies employ subjective measures of firm's performance [384]. There exists difficulty in obtaining financial data from small firms [385]. In addition, several studies provide the evidence that subjective measures of overall firm performance are closely associated with objective ones [385][386][387].

Miller and Cardinal investigated 35 previous studies and suggested the most popular performance variables: sales growth, earnings growth, deposit growth, return on assets, return on equity, return on sales, and return on total invested capital [374]. Standards for the firm's effectiveness, however, vary widely from industry to industry [388]. Consequently, the selection of a performance index is inevitably arbitrary. This research discusses the economic measures of firm performance.

2.9.1. Sales

The rationale for using sales as measures of business performance stems from the fact that despite several limitations, this measure has been extensively used in past research on examining the relationship between TF characteristics and business performance [378][388]. The most common indicator is sales growth. Growth in sales reflects how well an organization relates to their environment [389]. Many studies use sales growth as a measure of the extent to which a firm's innovative activities are stimulating revenue growth [310].

However, like other business performance measures, sales indicators have limitations. Sales indicators include total sales of a firm in certain period of time, sales



of new products, sales growth, sales per employee, and return on sales. Parasuraman and Zeren suggested that sales may be a more meaningful yardstick rather than profits or earning for evaluating R&D effectiveness [390]. Fulmer and Rue used the average of annual percentage sales growth experienced over the last three years [4]. The sales growth figures are normally based on nominal sales [303]. Morbey found a strong relationship between R&D spending and growth in sales [303]. Meanwhile, return on sales (ROS) fails to capture the relative effectiveness of the use of assets by the firm [391].

2.9.2. Revenue

Few studies have used revenue to measure a firm's business performance. Bracker and Pearson use revenue growth for financial performance data, which is the absolute annual percentage of growth rates during certain period of time examined [392]. Griffin and Page indicated that revenue can be used to measure customer acceptance in both one-year short and four to five-year long terms [382].

2.9.3. Earning

Thune and House measure financial performance with earnings per common share, which is the portion of a firm's profit allocated to each outstanding share of common stock [368]. Narin *et al.* measured the increase in average annual percent change in earnings per common share (current dollars) by a firm [307]. The earnings per share (EPS) are computed annual rates of change in percentage.

2.9.4. **Profit**

For the R&D effectiveness index, McGrath and Romeri suggested the new product profit, which can be calculated by multiplying the percentage of revenue from



products introduced in the last three years by the rate of net profit combined with the percentage of R&D spending [304]. Grabowski and Mueller use profit rates to determine profitability [393]. They examined the association between profit rates and R&D intensities. Leonard also focused on the association between the firm's profit and R&D intensity which is measured by R&D investment over net sales [381]. For the R&D effectiveness index from new products, McGrath Romeri suggested representative average profit from a new product rather than actual profit due to limited accuracy [304]. They also indicated difficulty in identifying the actual profit of individual products. Many studies use seven different types of profit for determining financial performance: profit of new products, total profits of a firm in certain period of time, profit margins, net income after tax, net worth, profit rates, and profit growth.

2.9.5. Return on Investment (ROI)

The private research sector is notoriously known for closely linking R&D with Return on Investment (ROI). The ROI approach is based on a comparison of the cost of R&D over a period of years with the earnings contribution by products from R&D for the period [287]. Unfortunately, accurate measurement of ROI on R&D is not a clear cut process. For measuring R&D effectiveness, ROI can be a misleading indicator which simply depends on a measure of net income or profit at a given time, not over a certain period of time [303]. In other words, ROI accounts for only present activities focusing on short-term profitability. Mechlin and Berg also pointed out that the use of ROI criteria might lead to a decrease in R&D spending [394]. One reason is that technological innovations usually take several years to produce a commercial success and could have unpredictable success [394]. For example, Westinghouse spent over 30



years developing a superconducting generator over 30 years [394]. Dupont took about ten years to introduce nylon products to customers [395]. Furthermore, it is significant to note that R&D spending is embedded in ROI, which may cause artifactual results due to variable construction [396]. Some studies provide the evidence to support positive relationship between market share and ROI [397][398]. Wagner identified nineteen factors, subgroup of three categories such as such as competitive and market factors, sales and expense ratios, and investment and employment ratios, which affect ROI [399].

2.9.6. Return on Equity (ROE)

Several studies employ return on equity as a measure for determining firm performance. Rhyne used 1-year return on equity (absolute and relative) to the planning [388]. Thune and House also measured financial performance in terms of return on equity [368]. Leontiades and Tezel used five different measures for investigating economic performance including return on equity (ROE) [366]. Robinson and Pearce employed a percentage change approach based on average performance over time in ROE [400].

2.9.7. Asset

After tax return on total assets is commonly regarded as one operational measure of the efficiency of a company regarding the profitable use of its total asset base [401][402]. Return on assets (ROA) is one of the easily obtained and widely circulated of firm financial performance measures [403]. Many innovation studies use ROA as a profitability measure [404][405][310]. Fredrickson and Mitchell used the average after tax return on assets for the most recent five years to assess financial performance [406].



Several studies used the average pretax return on assets (ROA) for the previous three-year period for measuring economic performance [407][408]. Baker suggested ROA measure rather than sales growth or return on equity, due to common usage as well as comprehensive financial measure [407]. He also pointed out that three-year average return on assets is a good compromise measure rather than one-year average return or over four-year average, due to time sensitivity as well as data availability. He also pointed out that three-year average return on assets is a good compromise measure rather than one-year average return or over four-year average, due to time sensitivity as well as data availability. ROA is a useful measure of how well the firm has used its funds [391]. Harling and Funk pointed out that ROA is free from the bias imposed by differences in capital structure caused by financial leverage through high debt/equity ratios [391].

Return on assets (ROA), however, has also limitations, since it is distorted by previous spending decisions [378]. Several previous studies use different types of assets index such as assets growth and net assets per share. Grinyer and Norburn used net assets per share to assess the effectiveness of planning on financial performance [409].

2.9.8. Stock

Kudla used stock returns on average as a measure of effects of formal planning on financial performance [371]. He argued that financial performance is measured by common stock returns, since much of business finance focuses on maximizing stockholder wealth. Several studies employ stock market value to determine the effects of planning on economic performance.



2.9.9. Market Share

It has been widely accepted that one of the major measure of business profitability is market share [397]. Market share is positively associated with financial performance [410]. For example, market share and ROI are strongly associated [397]. Gale found the positive relationship between market share and the rate of profitability [401]. Moorman used market share relative to its stated objective for measuring new product performance [411]. Deshpandé *et al.* also measured financial performance using market share [412]. However, market share, as an indicator, should be used carefully, since low market share is not necessarily indicative of poor performance by R&D community, as opposed to that high or growing market share almost certainly indicates effective technical efforts [413].



Table 24 The summary of outcome indicators from the literature

0.4			
Outcome Element	Indicators	Description	References
	Sales of new products	Percent of sales for new products for a certain period of time	[299][345][414][382] [306][362][349]
	Sales growth	Percent of sales growth of a firm in certain period of time	[303][415][381][368] [416][366][4][406]
	Sales volume	Total sales of a firm in certain period of time	[390][331][307][369]
Sales	Sales per	Percent sales per employee in certain period of	[415]
	employee	time (e.g. labor productivity)	
	Sales per share	Percent sales per share in certain period of time	[369]
	Sales per R&D	Annual sales per R&D budget	[349]
	Return on sales	Earnings after interest and taxes divided by total sales	[417]
Revenue	Revenue growth	Percent of revenue growth of a firm in certain period of time	[392][382]
	Earnings growth	Average annual percentage earning growth in certain period of time	[4][307]
Familia	Earnings/sales ratio	The average value of the earning/sales ratio over the last three years	[4]
Earning	Earnings/total capital	The average earnings/total capital over the last three years	[4]
	Earnings per share (EPS)	The portion of a firm's profit allocated to each outstanding share of common stock	[368][307][369][409]
	Profit of new products	Percent profit of new products in a certain period of time	[304]
	Profits	Total profits of a firm in certain period of time	[390][287][418]
	Profit margins	Percent profits of assets in a certain period of time	[415][400]
Profit	Net income after tax	Percent of revenue that reflected in net income after tax for certain period of time	[381][370]
	Net worth	Percent of revenue that reflected in net worth or profit for certain period of time	[381][419]
	Profit rates	After tax profit rate	[393]
	Profit growth	Percent of profit growth of a corporation in certain period of time	[420]
Return on Investment	ROI	Percent change of the ratio of net, pretax operating income to average investment for certain period of time	[399][398][349]
(ROI)	ROI of new products	Number of year from the beginning of the investment until it is paid off	[421]
Return on Equity	ROE	Net income divided by shareholder's equity	[373][368][366][400]
	Return on assets (ROA)	Net earnings before interest and taxes divided by total assets	[378][422][366][409] [400][407][406]
Asset	Assets growth	Percent of assets growth of companies in certain period of time	[381]
	Net assets per share	Net assets per share in certain period of time	[409]
Stock	Stock market value	Value of stock market of a company, stock price, change in the stock market value.	[368][416][288] [369]
SIUCK	Stock returns	Total return includes interest, capital gains, dividends and distributions	[371]
Market share	-	Percent of increased market share or the ratio of dollar sales by a business relative to its targeted objective in a given time period	[397][382][411][412] [347][349]



Chapter 3 Research Gaps

Few studies have attempted to explore the collective implications of technology forecasting within organization for its R&D performance and, ultimately, business performance. Furthermore, despite substantial interest in forecasting technology, little direct evidence to describe organizational/strategic aspects of a firm's TF activities with technology strategy has appeared in the literature. This study focuses on how systematic forecasting helps businesses make better strategic decision. This study found current research gaps in TF fields with respect to methodological, technological, organizational, financial, and industrial aspects as follows, even the list is not all mutually exclusive and exhaustive.

■ Methodological Aspects

- The relevance and availability of data and the appropriate selection of TF techniques are basic elements to improve the effectiveness of the forecast in strategic technology planning [52][423].
- Some scholars point out that combining different TF methods is significant means to improve the effectiveness of TF [23][24][25], but little statistical evidence to support the proposition exists.

■ Technological Aspects

• Little effort has been made to select an appropriate technique with the consideration of technology characteristics such as disruptive vs. incremental technology in technology planning [26][424].



- Discrete characteristics of technology require appropriate information pertaining to technology difference as well as TF methods well-suited for their purpose [52].
- The scarcity of empirical studies exists regarding how to select an appropriate technique for a particular technology [26].
- The choice of TF methods might depend on the type of R&D such as basic research, applied research, and commercialization.
- Organizational/Strategic Aspects
 - Little attention has been given to describe organizational/strategic aspects of a company's TF activities integrated with technology strategy for improving organizational performance.
 - The study is needed to identify the most efficient organizational structure of TF within a corporate for efficient management of technology.
 - The appropriate TF in technology planning could help the firm yield and sustain competitive advantages [52][425].
- Financial/Economic Aspects
 - The selection of TF methods also depends on the cost/benefit or the value of the forecast to the firm [423].
 - The failure to forecast changing market conditions is a major reason for the failure of some established companies in a variety of industries [426].



- Very little empirical research has been conducted to determine the impact of TF on the business performance of the firm in today's competitive environment.
- Application/Industrial Aspects
 - Special use and care should be taken to choose the proper TF method for a particular application [423].
 - There is a marked shortage of clear guideline as to where and how particular TF methods are useful in strategic planning based upon product and service characteristics or the nature of industry [26].

In consequence, this research identified that very little attention has been paid to the suitability and the effectiveness of TF methods in the literature.



Chapter 4 Research Objectives

The primary objective of this study is to investigate the effectiveness of technology forecasting in strategic decision making process for developing products and services based on exploratory approach. The strategic planning for technology development and a systematic integration process has become a significant issue. This study contributes to the identification of the degree of usability and usefulness of TF techniques for the development of products and services in practice. In order to do that, this research set questionnaires to the companies listed in manufacturing and engineering service industries.

The goals of the proposed research are:

- To identify technology forecasting tools in a strategic decision making process to develop technology, product and service.
- To provide a current snapshot of how firms across industries implement
 best practices in technology forecasting to facilitate organizational functions
 and strategic technology planning in the U.S. industrial firms.
- To help decision makers or forecasters select appropriate techniques in their business domains.
- To investigate if firms utilizing more sophisticated technology forecasting methods exhibit better R&D performance as well as business performance than firms utilizing less ones.
- To improve the effectiveness of technology forecasting in strategic planning by capturing technology characteristics in various industries.



- To provide an appropriate organizational decision making guideline to effectively implement in technology forecasting activities for supporting R&D planning
- To give recommendations to policymakers, researchers and other stakeholders to better develop and implement R&D projects in their country.

Each research goal has generated research questions pertaining to it. These research questions are in need of much more study.

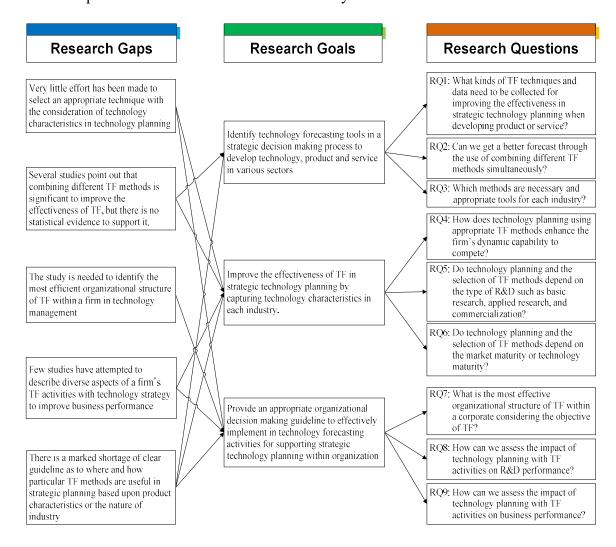


Figure 6 Research gaps to research goals and questions



Chapter 5 Hypothesis Development

This section of the study addresses the theoretical support for the development of the research hypotheses. Based on the prior studies and strategic management theory, eleven statistical hypotheses are formulated.

5.1. Technology Characteristics and the Effectiveness of TF

One of the most significant tasks is to select appropriate methods for a given situation, so as to predict the right technological change in a certain future, since the methods employed inevitably affect technology forecasting results [26][52]. It is theoretically inappropriate to use composite methods among them in order to solve practical forecasting problems, in case of that it has the conflict of assumptions based on them. If TF methods and data are matched and utilized appropriately to the nature of technology in a firm, the effectiveness of technology planning may become distinctive relative to those that are not. Cho and Daim [427], and Mishra et al. [26] indicated that a company should select proper technology forecasting methods based on the nature of the technology. Walsh concluded that the qualitative knowledge of technology is required to detect the emergence of major or radical innovations which may lead to rapid growth, due to the limitation of quantitative patent statistics [428]. Furthermore, several studies indicated that the type of R&D such as basic research, exploratory research, applied research, development, and product improvement influences measurement techniques and the metrics [296][349][429]. Likewise, a firm in slowly growing industries is likely to use methods applied to incremental and continuous technology, while as the firm in emerging industries or drastically changing business environments has a tendency to use tools applied to discontinuous (disruptive)



technology. For example, when historical quantitative data is not available, in most cases, qualitative data and tools are used to forecast emerging technologies.

Cho and Daim [427] identified TF methods according to exploratory and normative approaches, and analyzed application tools associated with the nature of technology such as disruptive/discontinuous and continuous technology. Their previous research helps to identify whether a firm use proper TF tools to predict technological changes for its strategic management of technology planning or not. Therefore, it is significant to note that it requires experience and expertise in various TF techniques to select appropriate forecasting methods. The majority of the previous studies applied qualitative approaches when considering radical or disruptive technology innovations, supporting this claim. In addition, qualitative approach has been used in many previous studies to forecast long-term technological changes. Based on these arguments, the following hypotheses are proposed for this research.

H1a: Qualitative data and technique would be preferable in radical technology innovation.

H1b: Quantitative data and technique would be preferable in continuous technology innovation.

Certain technology forecasting methods are employed concurrently to predict technological changes or innovation, but others are not. Many studies point out that a combination of different approaches and methods are required to improve the effectiveness of forecasting, since a combination of multiple techniques enables forecasters to analyze various perspectives (organizational, technological, economic,



political, personal, social, and environmental) [23]. There are a number of papers to use hybrid TF tools in order to offset weaknesses of one forecasting technique such as technology roadmapping with scenario technique [282], Delphi with cross impact analysis [283], bibliometric with growth curves and system dynamics [23], and technology roadmapping with morphological analysis and text mining [284], etc.

H2: Combining multiple methods simultaneously has a positive relationship with the effectiveness of TF.

TF is critical to all firms. However, in mature industries, research and technology development tends to be applied to existing product extensions and to process refinements as competitors try to reduce their production costs [316]. Life cycle of a product depends on the industry. High-tech industries like electronics have a short life cycle compared to low-tech industries like cement [430]. Abernathy and Townsend indicated that technological inputs have the least impact where they are needed most, in mature or stagnant industries [431]. In industries where technological innovation is significant, R&D capabilities may be the lead ones in defining the dynamic capabilities of a firm [350]. Technology forecasting in technology planning is a critical step to follow before developing the technology. Therefore, this research claims that the use of TF techniques will be different across industry sectors.

H3: The use of TF techniques differs across sectors.

Tushman, Abernathy and Utterback made arguments that it is significant to understand life cycle of innovation or technology, which helps a firm predict the timing



of radical change [430][432][426]. Several studies describe innovation streams in both incremental and discontinuous innovations, which illustrate the evolutionary cycle of innovations with technological discontinuity phase, dominant design phase, and retention phase [426][430]. If a firm manages innovation and change, it must acknowledge about these streams of innovations. During the dominant design stage, R&D efforts shift from major product innovation to process innovation and incremental innovation [433]. In this phase, technology monitoring and TF activities in technology or strategic planning would be reduced compared to technological variation phase. These hypotheses are based on the belief that TF activities within a firm are more inclined to focus on radical innovations rather than incremental innovations from R&D efforts due to increase of uncertainty and risk on business environment.

H4: TF activities differ across the type of innovation the firm creates.

5.2. TF and Technology Planning

Technology forecasting has evolved as a means for strategic planning in a firm [434]. Erich Jantsch categorized the scope of technological forecasting into three planning levels: policy planning, strategic planning, and tactical planning [59]. At the strategic planning level, TF is used to enrich this basis for strategic selection [59]. For tactical planning, TF involves in the probabilistic assessment of future technology transfer [59]. At policy planning level, TF more focuses on basic scientific-technological potentialities and limitations as well as ultimate outcomes in a large systems context [59]. Firms must be able to integrate technology planning with strategic planning so that they may deal with technological evolution [376]. R&D managers and



other senior management group work together to formulate and execute complementary technology and strategic plans [376]. TF plays a crucial role in developing a technology plan [376]. A variety of use of TF makes it difficult to measure its contribution as a source of R&D performance and business performance. R&D funding is allocated through technology forecasting, technology evaluation for project selection, technology strategy, to strategic planning.

Technology planning is critical both for cost-competitiveness and differentiation in business strategies [435]. TF plays a significant role to identify areas for research in many firms during planning process [436]. Frederick Betz also described TF as a critical step in technology and business planning to predict and implement technological changes in a firm with the consideration of new product development, production, and marketing [437]. It is significant to note that a structured process for technology planning should be established in a firm [438]. This process helps a firm to identify its competitive advantage by providing a picture of R&D's role in business success. Technology forecasting is needed to predict promising alternatives as well as to assess alternatives in planning process [439]. Technology forecasting, technology planning, technology strategy, business strategy, product lines, and R&D funding are tied together.

H5: The use of TF has a positive relationship with technology planning activities in a firm.

Meanwhile, it is theoretically inappropriate to use composite methods among them in order to solve practical forecasting issues, owing to conflicts of assumptions.



Firms in slowly growing industries are likely to use methods applied to incremental and continuous technology, whereas firms in emerging industries or drastically changing business environments have a tendency to use tools applied to discontinuous technology. For example, when historical quantitative data is not available, in most cases, qualitative data and tools are used to forecast emerging technologies.

Accordingly, experience and expertise in various TF techniques is important in selecting the appropriate forecasting models. The firm's competitiveness would be perceived to be associated with the contribution of strategic technology planning efforts with the appropriate use of TF.

H6: The appropriate use of data and TF methods improves the firm's capability for technology planning activities.

5.3. Firm Size and TF Intensity

Due to fixed costs of R&D, some minimum size is required before a firm can maintain effective R&D program [440]. If larger firms possess relatively more resources and assets such as financial capabilities, commercialization assets, and strong marketing assets to exploit technological opportunities, they should benefit more from TF activities. When examining manufacturing firms, economies of scale and experience should be considered, which leads for larger firms to greater efficiency in production process [441]. Furthermore, large firms may be better able to retain qualified staff who might be tempted to forecast emerging technologies.

There are still controversial debates on whether propensity rate to patent increases with firm size in the literature. Some studies report that small firms have more



propensities to file a patent than larger ones [442]. Halperin and Chakrabarti found that R&D productivity has a negative association with firm size [331]. Although this proposition sounds reasonable, there has been weak evidence to support this proposition, however [443][338]. Other studies found the evidence that firm size affects the probability of conducting R&D [444]. Scherer proposed that patents have slightly positive association with larger companies [299]. Arundel and Kabla also found the evidence in favor of positive relationship between patent productivity and firm size [313]. Consequently, this study makes a proposition that there is a positive association between firm size and TF activities in planning processes.

H7: The size of a firm has a positive relationship with TF activities in planning processes within organization.

Small- and medium-sized enterprises (SMEs) are important sources of innovation. A small firm, however, may be technically and managerially quite competent yet unable to absorb new technology easily because of the extra demands placed on its scarce managerial and technical manpower [445]. Small firms are vulnerable to technological changes in their competitive environment. Due to lack of resources, SMEs will experience more intense competition on their market. Finally, large firms will have a propensity to be more R&D intensive than small companies. In sum, this study suggests that small and large firms can benefit from technology forecasting activities in the United States. Large firms, however, seem to derive considerable benefits from not only internal TF activities, but also external TF sources.



Because of lack of internal resource, small firms can have a propensity to gain benefits from mainly external TF resources.

H8: The use of internal/external TF sources differs across the firm size.

5.4. Technology Planning and R&D Performance

High internal planning capability enables a firm to more effectively select R&D projects that present themselves fulfilling technological changes. Careful forecasting clearly identifies customer's technological needs, and the technological threats and opportunities relevant to the firm's strategic goals [436]. Baker *et al.* suggested that the success of R&D projects highly depends on how to resolve the initial uncertainty associated with their technical and commercial goals and objectives [446]. Although R&D progress depends on non-technical factors such as investment, staff size, facilities, morale, and top management support [447], it appears reasonable to expect that systematic forecasting exhibits differing degrees of effectiveness on R&D.

On the other hand, technical performance can be used as a measure of R&D. Technological inventions and innovations have been playing a significant role for a firm to compete in the targeted market. Patents would be regarded as the output of technically successful R&D activities. Scherer suggested a positive relationship between patents and R&D investment in the U.S corporations depending on industry sectors [299]. The more R&D intensive firms have a greater tendency to patent [305]. There have been discussions in the literature as to whether patents are simply an indicator of R&D expenditure, or whether they measure the output of invention, however.



Objective probability of success ratings from technology forecasting on selected R&D projects in technology planning process is correlated with the eventual success and failure of these projects. Consequently, this research aims to investigate the effect of technology planning with TF on the R&D performance based on the proposition that technology planning activities will be positively related to R&D performance.

H9: R&D performance has a positive relationship with technology planning activities in a firm.

5.5. Technology Planning and Business Performance

The participation of TF in long-range company goals setting is a good indicator of the degree to which R&D is integrated into the company as a whole [448]. With deliberate attention to this, technology should be managed strategically. Quinn and Mueller emphasized that a systematic planning process and management skills are required not only to align R&D efforts with the company's business goals, but also to effectively transfer research results to commercial success [449]. Roy Rothwell pointed out that good technology planning and management techniques are one of the success factors for innovation [450]. However, the empirical evidence for such a claim is thin.

TF plays various roles in formulating business strategy [9] as well as setting long-term goals. Technological opportunity captured by technology forecasting must have market reference. Cooper indicated that top performing firms possess the most active idea search efforts of all firms to identify market needs, while poor performing firms have the most passive of all idea search efforts with the weakest R&D orientation



of all firms [362]. A firm with poor planning has a tendency to look for derivatives of existing products, or reacting to a competitors' moves [451]. It has little idea about what its business will be like in five years. A series of empirical studies have provided mixed support for the association between corporate planning and business performance [373][4][371]. Despite the wide recognition of the importance of technology planning, the association between technology planning and business performance has not, in general, been well documented empirically in the literature. A great majority of technology planning literature deals with how to plan and not the effects of R&D planning. Very little practical guideline for technology planning has been introduced to determine the effectiveness of technology planning on the business performance of the firm. This hypothesis is based on the belief that firms which have systematic technology planning activities are more likely to identify opportunities and threats that could significantly result in commercial success from R&D efforts in the operation.

H10: Business performance has a positive relationship with technology planning activities in a firm.

5.6. R&D Performance and Business Performance

R&D investment is one of diverse factors which can affect the sales growth and profitability in a firm. The firm should make R&D a strategic force in its growth and competitiveness [285][376]. There is no question about that low profit would be likely to lead to low R&D expenditure. Profit and R&D have a recursive association one another [311]. Some scholars suggested the tenuous association between R&D expenditure and growth in profitability [303][399], although R&D should be designed



Also, despite the success of technological development, there might be failure from lack of management skills or market knowledge to make a profit out of it [425]. However, investing in future technologies can prove to have ROI with the prospect of licensing loyalties. The important thing is how to capture expected returns from R&D. The question on the association between patents and financial performance remains unresolved depending on the research scope and design, specifically at the firm level [452]. The more patents, however, lead to subsequent change in business performance such as sales growth, or profit increases [383][342]. The new invention should lead eventually to the generation of financial profit. In sum, financial performance relative to a firm's industry will be positively related to R&D performance.

H11: R&D performance has a positive relationship with business performance of a firm.

These research hypotheses derived from the literature review are summarized in Table 25 as follows.



Table 25 Research questions and hypothesis

1 71					
Research questions	Hypothesis				
RQ1: What kinds of technology forecasting data and techniques need to be collected for improving the effectiveness in strategic technology planning in order to develop product and service? RQ2: Can we get a better forecast through the use of combining different TF methods simultaneously? RQ3: Which methods are necessary and appropriate tools for each industry?	H1a: Qualitative data and technique would be preferable in radical technology innovation H1b: Quantitative data and technique would be preferable in continuous technology innovation H2: Combining multiple methods simultaneously has a positive relationship with the effectiveness of TF H3: The use of TF techniques differs across sectors				
RQ4: How does technology planning using appropriate TF methods enhance the firm's capability to compete? RQ5: Does technology planning and the selection of TF methods depend on the type of R&D such as basic research, applied research, and commercialization? RQ6: Does technology planning and the selection of TF methods depend on the market maturity or technology maturity?	H4: TF activities differ across the type of innovation the firm creates H5: The use of TF has a positive relationship with technology planning activities in a firm H6: The appropriate use of data and TF methods improves the firm's capability for technology planning activities				
RQ7: What is the most effective organizational structure of TF within a corporate considering the objective of TF? RQ8: How can we assess the impact of technology planning with TF activities on R&D performance? RQ9: How can we assess the impact of technology planning with TF activities on business performance?	H7: The size of a firm has a positive relationship with TF activities in planning processes within organization H8: The use of internal/external TF sources differs across the firm size H9: R&D performance has a positive relationship with technology planning activities in a firm H10: Business performance has a positive relationship with technology planning activities in a firm H11: R&D performance has a positive relationship with business performance of a firm				



Chapter 6 Research Design

Technology forecasting activities and TF techniques can be considered differently based on managerial levels within a corporation, organizational structures, firm size, and industry sectors. This study attempts to examine the association between several dimension of the technology forecasting such as methodological, organizational, technological, industrial, organizational, and economic aspects.

To perform this study, it is necessary to identify the firms that are engaged in technology forecasting activities. The only feasible technique for collecting this information is survey. Using survey instrument, the purpose of the study is to analyze the effects of technology forecasting activities on R&D performance in manufacturing sectors, with a special emphasis on technology planning, and to assess technology forecasting on business performance through R&D performance. For the comparison among industries, therefore, the study will explore major industries dealing with technology forecasting such as manufacturing, communication, and professional, scientific and technical services with respect to TF activities, since the lifecycle of technologies in these industries are transparently different. Along with that, technologies can be intertwined to meet the market requirements in some fields. This research aims to reveal the extent of use of TF methods in the U.S. industry.

The interest of this study is in causal structure. This study proposes that R&D performance serves as a moderator of the association between technology forecasting and business performance in a firm. Base on the literature, the structural equation model is developed concerning both the impact of R&D performance on business performance and implications about technology forecasting returns to internal planning in a firm.



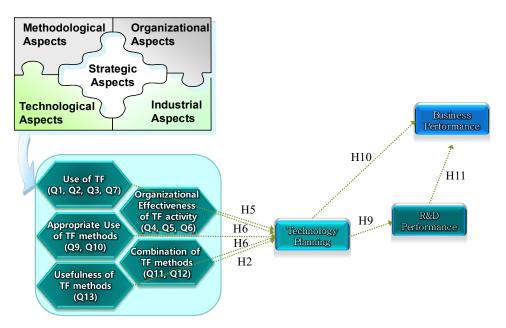


Figure 7 Research model



Chapter 7 Research Methodology

In this study, structural equation model (SEM) is used to test hypotheses proposed in Figure 7 in previous section because SEM is appropriate to analyze path model with latent variables in order to uncover causal structures. The hypothesized relationships in this model have multiple intercorrelations between a set of variables, which are developed based on literature review and hypothetical assumptions. A straight, one-headed arrow represents a causal association between two variables. This model cannot be solved by ordinary least squares regression techniques. Multiple regression can be regarded a special case of SEM [453]. By contrast, SEM approach is a multivariate tool that takes into account complete and simultaneous equation of all relationship in a given model. SEM approach allows us to easily articulate relationships of all variables with one another [454].

7.1. Path Analysis

This research focuses on the causal inference in latent variable models. Causal relationship is the focal point of SEM analysis [453]. Path model incepted in population genetics to model inheritance by Sewall Wright in 1918 [455] and later widely applied to various situations in psychology and sociology [456]. Path models and multiple regression provide the core information needed to understand the broad class of SEM [454]. Path analysis gauges the strength of causal relations among variables in a multiple systems of equations based on the correlation matrix of observed variables [457]. In the 1970s cross-disciplinary integration ended up with structural equation modeling. SEM mainly deals with the specification of causal relations among variables. Path analysis in SEM has become one of the most widely used techniques to investigate



the direct and indirect effect of causal variables on dependent variable [458]. In causal relations, mediation is a hypothesized causal chain in which one variable affects a second variable that, in turn, affects a third variable [459]. The indirect effect represents the portion of the relationship between X and Y that is mediated by M (mediator or mediating variable or intervening variable) [460]. By contrast, moderation is a hypothesized causal chain in which one variable affects the direction and/or strength of the relation between an independent variable and a dependent variable [461]. In recent years, SEM has been advanced by incorporating additional statistical models such as growth models, generalized linear models, and multi-level models [462]. In conclusion, SEM allows researchers to examine theoretical propositions with respect to how factors are theoretically interrelated and directionality of associations among variables.

7.2. Factor Analysis

Path modeling is integrated with logic of factor analysis [454]. Based on the groundwork Karl Pearson and Charles Spearman made in 1900s, factor analysis was developed to explore the structure of intelligence in multivariate data [462]. Factor analysis has been widely used for the analysis of correlated data [463]. Factor analysis is designed to link factors to measures that are defined in terms of weights [454]. The construct of achievement in a factor is defined by what those measures have in common [454]. The applications of factor analysis can be categorized into two different approaches such as common factor analysis and principal components analysis, which help to examine the variance for a given variable relative to other variables in the data set [463]. There are exploratory factor analysis (EFA) and confirmatory factor analysis



(CFA) to examine the internal reliability of a measure. These techniques are used to investigate the theoretical constructs, or factors, that might be represented by a set of items. Both are used to assess the quality of individual items.

EFA has been a widely used method to determine the number of factors to retain, which explain the variation and covariation in a set of measured variables [464]. EFA can be used to evaluate construct validity [465]. EFA play a role in not only evaluating variables preliminarily, but also developing and refining the instrument's scales [465]. EFA is often employed when researchers have no hypotheses about the nature of the underlying factor structure of their measure [466]. EFA is pragmatic rather than theoretical in use. EFA has basically three steps: deciding the number of factor, choosing an extraction method, and choosing rotation method. At first step, the most common technique to decide the number of factors is generate a scree plot [467]. Once the number of factors is determined, the researcher runs factor analysis to identify the loadings for each of the factors. For factor extraction, principal components analysis (PCA) is widely used, which assumes there is no measurement error. However, Snook and Gorsuch suggested that PCA generate better estimates of population loadings with larger samples, and poor estimates in small samples [468]. Finally, after an initial solution is obtained, the loadings are rotated. Rotation is a way of maximizing high loadings and minimizing low loadings in an attempt to attain the simplest possible structure [466]. The researchers must decide what type of rotation to use. Newsom recommends promax rotation since it is known to be relatively efficient at achieving simple oblique structure.



On the other hand, CFA is differentiated from EFA. CFA requires the specification of particular factor structure, whereas EFA allows all items to load on all factors [466]. In other words, with CFA, the research should specify which items load on which factor a priori. CFA examines a fit of the hypothesized factor structure to the observed data [454]. CFA approach attempts to examine whether or not observed data are consistent with the posited theoretical model. CFA provides a chi-square test and goodness-of-fit indicators. CFA is more theoretical than pragmatic. CFA is a specific instance of the general structural equation model [469]. The difference between CFA and SEM is that unmeasured constructs are hypothesized to be causally interrelated, whereas they are intercorrelated in CFA models [454]. CFA has become popular with the aid of statistical software package since late 1970s [454].

When researchers implement the model which departs from the posited theoretical model, it is recommended to use both CFA and EFA along the continuum in some circumstances [469]. Each method has some advantages and drawbacks. Therefore, researchers can use each method for a complementary purpose.



Chapter 8 Data Collection

This chapter describes the data collection process, which covers survey design, instrument validation, instrument administration, targeted population, sampling strategy, and response rate.

Surveys can be administered by online, mail, phone, fax, or in-person, and there are different questionnaire considerations for each mode. Electronic using internet is the easiest to administer and tabulate, but most susceptible to "survey fatigue." Paper or mail adds additional layer of confidentiality, but less efficient medium for tabulating results. Telephone is easier to tabulate than paper, but increasingly difficult to administer due to cell phones because cell phone numbers are much less tied to where people geographically live [470]. Cobanoglu, Warde, and Moreo compared mail, fax, and web-based surveys with respect to response rate, response speed, and costs [471].

Internet web-based survey has become popularized in form of surveying in the world because it allows researcher to conduct the survey with speed, low cost, flexibility, easy execution, convenience, and economies of scale, when compared to traditional telephone or mail methods [472]–[475]. On the other hand, a mixed-mode strategy has been suggested as a means to improve response rates [476]. The comparison of each survey mode is summarized in detail in Table 26.



Table 26 Comparison of mail, fax, and web-based surveys

Factor	Mail	Fax	Web-based
Coverage	High	Low	Low
Speed	Low	High	High
Return cost	Preaddressed/Pre-stamped	800 return fax number	No cost
Incentives	Cash/Non-cash incentives can be included	Coupons may be included	Coupons may be included
Wrong addresses	Low	Low	High
Risk of delivery failure	Medium	Medium	Low
Labor needed	High	Medium	Low
Expertise to construct	Low	Medium	High
Perceived urgency	Low	Medium	High
Level of detail	Low	Low	High
Cost effectiveness	Low	Low	High
Variable cost/ each survey	About \$ 1.00	About \$ 0.50	No cost
Cost/response	\$4.78	-	\$0.64

Source: adapted and modified from [471][477][478][479]

Internet surveys are suitable for tremendous survey efforts and for the larger targeted populations that are difficult to reach with traditional survey methods

[474][473]. Survey would be difficult to reach out to corporate executives in any method other than internet survey [480]. People with high level of computer ability—corporate executives and policy experts—are more likely to respond by online survey [472]. On the other hand, Kaplowitz, Hadlock and Levine found the largest response rate difference between the mail and the email only distribution mode [481]. Dillman *et al.* suggested that switching to a second mode is an effective means of improving response [482]. In this research, however, due to enough responses from email invitations and time constraints, follow-up fax invitations to participate in a web-based survey were not sent out to remaining respondents. In this study, a web-based survey



questionnaire was developed and was conducted to uncover the relationships between TF activities, organizational effectiveness, R&D performance, and business performance.

8.1. Survey Design

For self-administered survey, the design of the instrument is significant to obtain unbiased answers from respondents [483][484]. Form and graphic layout of the questionnaire are particularly important. A web survey should be designed with the survey population in mind [472]. In this study, firms that have invested R&D for the new product or service development are included in the survey. The web-based survey questionnaire was designed and sent to a person who has a high probability of being acquainted with technology forecasting within organization such as CEO, Vice President of Engineering, CTO or R&D Manager. These survey respondents would be expected to have a high level of technical proficiency with both the internet and mobile device [472].

i. For the construct validation, prior to administration, a web-based survey was administered to the expert panel to evaluate the survey using focus group interviews and cognitive interviews. Pre-test has been informed by theoretical work in the area of cognitive psychology [485][486] and social psychology [487][488]. The cognitive processes is to probe the subjects' internal states by verbalizing thoughts and feelings as they examine information in order to reduce measurement error by evaluating and improving survey questions.



ii. To validate the content, a web-based survey was administered to the expert panel to validate the instrument that will be emailed to targeted respondents.

8.1.1. Survey Layout and Usability

The web-based survey instrument is comprised of three elements:

- i) Introduction page: This page describes the objective of this study, and includes the consent form along with instructions for taking the survey. It also incorporates asking the intention to receive the summary results of this study to appeal interest in this research and optional contact information section for further question about this survey.
- ii) The survey question: This page includes 14 survey questions and an optional section about a reward. The final survey questionnaire is presented in Appendix B.
- iii) Termination page: This page gives a short message notifying the respondent that the survey is successfully submitted, giving gratitude to them for this survey.

A variety of errors involved in survey method is illustrated in Figure 8. Therefore, it is critical to reduce or remove the error that might occur at each stage.



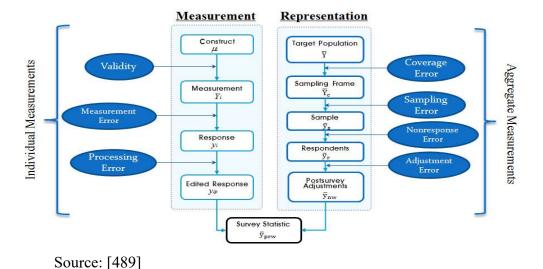


Figure 8 Sources of errors for a survey research design

Dillman proposes 32 principles to help reduce sampling error, coverage, measurement, and non-response in the survey with respect to web-based survey and mail [472][490]. These principles are helpful to enhance the usability of a survey. As presented in Table 27, the layout of web survey is designed, following some part of Dillman's guidelines [472]. The designed web survey is graphically illustrated in Figure 9 and 10.



Table 27 The design process of web survey

Guidelines	Description
G1	Create interesting and informative welcome and closing screens that will have wide appeal to respondents
G2	Use a consistent page layout across screens and visually emphasize information that is essential to completing the survey while deemphasizing inessential information
G3	Allow respondents to back up in the survey
G4	Do not require responses to questions unless absolutely necessary for the survey
G5	Do not include a graphical progress indicator
G6	Allow respondents to stop the survey and finish completing it at a later time
G7	Ask one question at a time
G8	Use specific and concrete words to specify the concepts clearly
G9	Use complete sentences that take a question form, and use simple sentence structures
G10	Organize questions in a way to make it easier for respondents to comprehend the response task
G11	Separate optional or occasionally needed instructions from the question stem by font or symbol variation
G12	Provide a single answer box if only one answer is needed
G13	Provide answer spaces that are sized appropriately for the response task
G14	Align response options vertically in one column or horizontally in one row, and provide equal distance between categories
G15	Group related questions that cover similar topics together
G16	Begin with questions likely to be salient and interesting to nearly all respondents
G17	Place sensitive or potentially objectionable questions near the end of the questionnaire
G18	Restrain use of color to improve readability
G19	Provide specific instructions and clarifications as needed for each question

Source: adapted from Dillman [472]





Figure 9 Introduction page of the survey

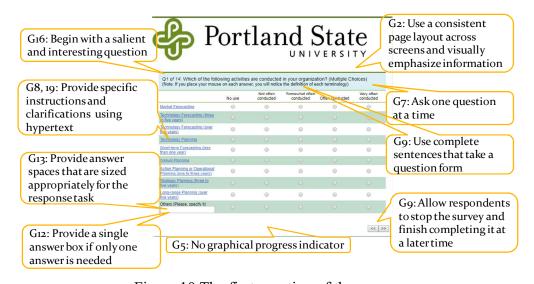


Figure 10 The first question of the survey

8.1.2. Delivery Method: Email

The web-based survey questionnaire was emailed to targeted samples with the invitation to take this online survey by clicking on a proper Uniform Resource Locator (URL) link. Respondents can access to web survey through their computers or mobile



devices with an internet connection. As described in Table 28, the layout of invitation email was designed, following parts of Dillman's guidelines [472]. The designed invitation email is graphically illustrated in Figure 11.

Table 28 The design invitation email

Guidelines	Description			
G1	Create an integrated look and feel between the email invitation letter and the			
	web survey			
G2	Appeal to respondents, whereby responding they would be helping complete			
	important research			
G3	Emphasize the survey is anonymous			
G4	Highlight the prize drawing to entice respondents			
G5	Provide clear instructions for how to access the survey			
G6	Have the survey web address jump out when viewing the email			
G7	Emphasize that the survey is short and will not be time consuming			
G8	Highlight that the request is from an academic institution, rather than, from a			
	marketing business firm.			
G9	To the extent possible, personalize all contacts to respondents			
G10	Keep e-mail contacts short and to the point			
G11	Carefully select the sender name and address and the subject line text for			
	email communications.			
G12	Take steps to ensure that emails are not flagged as spam			
G13	Work within the capabilities and limits of the web server(s)			
G14	Provide contact information in case there is a need for recipients to contact			
	researcher			

Source: adapted from Dillman [472]



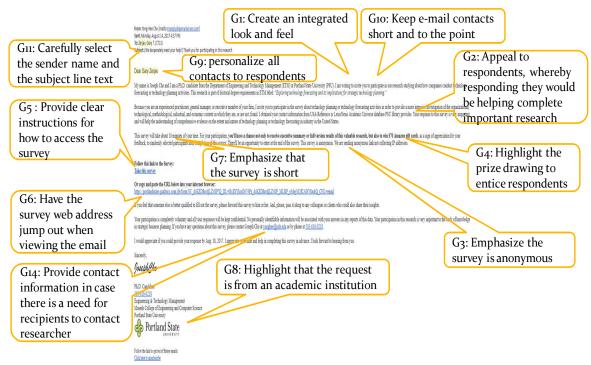


Figure 11 Invitation email

8.2. Instrument Validation

Prior to survey administration, survey contents and constructs should be validated by experts who make a judgment about survey items. To begin with, the Question Understanding Aid (QUAID)¹⁴ was used to evaluate syntax and test to flag some common problems with survey questions. Thereafter, to investigate the degree to which a measure appropriately represents what it is intended to, this research uses two approaches: content validity and construct validity [480].

Content validity. This measures the extent to which the content of each survey item accurately and comprehensively represents the content to be evaluated. For content validity, this study uses several tools such as literature review, cognitive interview, and

An interactive version of the software is available at: http://mnemosyne.csl.psyc.memphis.edu/QUAID/quaidindex.html



expert panel. The typical way to measure content validity is to utilize experts' judgments. To assess the measurement of content validity for this survey, the expert panel was formed and their judgments and opinions were collected. More details are discussed later in this chapter.

Construct validity. This is related to the question what construct, trait, or concept underlies a respondent's score on a measure [491]. Construct validity is established by assessing convergent and discriminant validity [492]. This specifies the domain of the construct, and generates specific items represent the domain. It requires internally consistent or internally homogeneous set of items. In this regard, researchers should determine the degree to which the measure correlates with other measures designed to assess the same construct, which is convergent validity. Discriminant validity is the degree to which the measure is not correlated with other measures designed to assess different constructs. For construct validity, this research uses several techniques: literature review and expert panel. To evaluate the measurement of construct validity for this instrument, the expert panel was formed and their judgments and opinions were incorporated. More details are discussed later in this chapter.

Pre-test has been informed by theoretical work in the area of cognitive psychology [485][486] and social psychology [487][488]. The cognitive processes is to probe the subjects' internal states by verbalizing thoughts and feelings as they examine information in order to reduce measurement error by evaluating and improving survey questions. Questions that are misunderstood by respondents or that are difficult to answer can be improved prior to fielding the survey. Pre-testing is the opportunity to see what questions work well, what questions sound strange, what questions can be



eliminated and what needs to be added. Thereafter, the expert panel is supposed to review model development and content validation. Expert panel is consisted of potential survey respondents to evaluate the survey. Cognitive interview was conducted to reduce response error such as interpretive errors and recall accuracy covered in this way.

It can be achieved by administering the survey to a few potential respondents (or your friends) to get feedback, and ask people to think out loud as they are answering the survey questions and probe them by questioning "What does that mean to you?", "How well each survey question presents the intention of the measurement", and "How well constructed is it for targeted population to answer each question". In evaluating a question's performance, cognitive testing examines the question-response process that is consisted of four basic stages: comprehension, retrieval, judgment and response, which is mainly credited to Tourangeau [485]. Some errors are also involved in this process as described in Table 29. In 1991, Edwards and Cantor suggested a modified five-step process adding encoding [493], while Willimack and Nicholes proposed three step modifications to the basic four step cognitive model inductively based on results of exploratory research [494].

Table 29 Cognitive model of question-response

Cognitive Stage	Definition	Errors involved	
Comprehension	Respondent interprets the question	Attending to and interpreting survey questions (careless responding)	
Retrieval	Respondent searches memory for relevant information	Generating a retrieval strategy and retrieving relevant beliefs from memory (confirmation bias)	
Judgment	Respondent evaluates and/or estimates response	Integrating the information (Biased or sensitive, Estimation Difficulty) into a judgment	
Response	Respondent provides information in the format requested	Mapping the judgment onto the response scale and answering the question (acquiescence)	

Source: [485]



8.2.1. Instrument Validation Plan

The survey instrument was validated in five steps, resulting in five survey questionnaire revisions over a 10 month period. The survey instrument was modified as necessary in accordance with expert panel's feedbacks and judgments. The instrument validation procedure is presented in Figure 12. The detail description of each step is as follows.

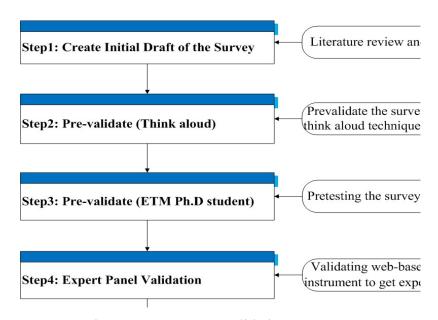


Figure 12 Instrument validation processes

i) Step 1: Create initial draft of the survey

Initial version of web-based survey was created based on literature review and brainstorming with both Ph.D. students and the dissertation committee.

ii) Step 2: Pre-validate (Think aloud)

The initial draft of survey was administrated to a group of Ph.D. students at the Department of the Engineering and Technology Management at PSU by employing the think aloud technique in order to obtain their feedback and comments. While they were going through all questions, they were asked to think aloud; to tell the interviewer all

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they read and what they are thinking about at every time [472]. Based on their feedback, the second version of the survey was made.

iii) Step 3: Pre-validate (ETM Ph.D. students)

At this stage, the second version of the survey was administered to a group of Ph.D. students at the Department of Engineering and Technology Management to prevalidate for completeness and quality of the second version of the survey. Based on their feedback, the third version of the survey was developed.

iv) Step 4: Expert panel validation

A validation tool was developed, based on the third version of survey questionnaires, to obtain experts judgment on the relevance of each question to its intention and the ease of answering each question. At this step, instrument validation was conducted by asking expert panel to evaluate each survey items. The first question is that "how well each survey question presents the intention of the measurement". The second question is that "how well constructed is it for targeted population to answer each question". The validation tool was administered to an expert panel of 79 members who agreed to participate in this survey validation process. Finally, 37 experts responded and gave their feedbacks on survey items. Based on their feedback, the fourth version of the survey was created.

v) Step 5: Pilot test the survey to the subset of potential respondents

Prior to survey administration, the fourth version of the survey was incorporated into a web-based survey and a link was emailed to a subset of expert panel by asking them to complete the survey and provide overall feedback on the content. At this step, the survey instrument was verified with a subset of potential respondents. The



pilot survey instrument was administered to an expert group of 79 members. Finally, 32 experts responded to this pilot test and gave their feedbacks on survey items. For further investigation, cognitive walkthrough method such as one-on-one interview or email discussion was used to obtain their feedback and comments on the survey.

8.2.2. Expert Panel Design

It is important to select appropriate experts who have a sufficient level of knowledge and experience on the subject matter for incorporating valuable and various perspectives. Prior research provides several criteria that can be used in forming the expert panel [495][496]. In this research, expert panel that composed of CEO, CTO, Vice President of Engineering or General Manager in a firm was formed to validate the survey instrument and clarify survey questionnaires. Experts were selected based on following criteria:

- Expertise in strategic decision making process for technology forecasting,
 R&D planning, strategic planning, and long-term planning from various
 sectors of U.S.-based manufacturing industries.
- Ensure the reduction of measurement errors by selecting the experts from different sizes such as small, medium, and large-sized companies.
- Easy to contact and get the feedback on the survey instrument
- Represent objective viewpoint in a firm to safeguard for individual biases on the results.

Initially, 6,563 expert panel candidates were contacted with an invitation email for the selection of expert panel. 79 experts agreed to be panel members. Finally, 37 experts participated in validation process of the survey instrument as listed in Table 30.



Table 30 Expert panel

No.	Title	Company	Location
1	CTO	Metacog	Worcester, MA
2	Sr. Vice President	Rockford Ball Screw	Rockford, IL
3			
3	CEO	Jamison Door Company	Hagerstown, MD
4	CTO, Worldwide IBM IT Economics Practice	IBM	Farmington Hills, MI
5	Director, Business Development & Licensing	Medtronic	Mansfield, MA
6	CTO & VP Engineering	Socket Mobile, Inc.	Newark, CA
7	Director of Systems and Strategies	Quantum Technology Sciences, Inc.	Indialantic, FL
8	Chief Technical Officer	K2 Energy Solutions	Henderson, NV
9	VP	SUMCO	Phoenix, AZ
10	VP - R&D	IEM Power Systems	Jacksonville, FL
11	Director of Technology	VersaLogic Corp.	Tualatin, OR
12	VP Engineering	Microbest Precision Turned Components	Waterbury, CT
13	Executive Director	Micro Systems Engineering, Inc.	Lake Oswego, OR
14	Engineering	Sargento Foods Inc.	Elkhart Lake, WI
15	VP Engineering	Watchfire Signs	Danville, IL
16	CTO	Exterro	Portland, OR
17	VP Engineering/CTO	Univision	New York, NY
18	R&D Director	The Procter & Gamble Co.	Cincinnati, OH
19	Chief Digital Officer	Hart Energy Publishing Lllp	Houston, TX
20	Director of Business Solutions & Pathfinding	Intel	Hillsboro, OR
21	Director Engineering & Asset Reliability	Sapa Extrusions North America	Monument, CO
22	Director	Matheson	Humble, TX
23	Director of Advanced Technology	Thermo Fisher Scientific	Hillsboro, OR
24	Senior Analog Design Manager	Microchip	San Jose, CA
25	Manager Project Management	Leviton Manufacturing Company, Inc.	Tualatin, OR
26	Director of Business Development	DeltaTrak Inc.	Pleasanton, CA
27	Director of Strategic Accounts	SP Controls	S San Francisco, CA
28	СТО	Source Photonics	West Hills, CA
29	Director, Product and Market Dev.	ZOLL	San Jose, CA
30	Manager Engineering Design	AT&T Inc.	Dallas, TX
31	Manager of Software Development	Vital Images, Inc.	Minnetonka, MN
32	R&D Manager	Voith Fabrics Inc	Appleton, WI
33	CEO	Global Packaging Machinery Co., Inc	Paterson, NJ
34	Director R&D	Serim Research Corp	Elkhart, IN
35	CEO	Arrington Performance	Martinsville, VA
36	CTO	Cengage	Boston, MA
37	VP Engineering/ CTO	Millar Inc.	Houston, TX



8.2.3. Step 1: Create Initial Draft of the Survey

As a first step, this study reviews the literature to develop initial draft of the survey instrument with respect to technology forecasting and technology planning as summarized in Table 31. This study attempted to identify various aspects of TF related to technology planning and firm performance from prior research employing similar types of methods.

Table 31 Prior research that was used as references in the literature

Topic	Methodology	Implications	Date
Matching of TF	Survey, scoring	- Identify TF methods for IT,	2002
technique to a technology	model, and	MBT technologies	
[26]	expert-based	- Identify variables and	
	decision	characteristics affecting tech.	
Identifying TF methods	Fuzzy AHP,	Identify TF methods for the	2008
for predicting the new	survey	new materials development	
materials development			
[424]			
Choosing a TF method	Situations	Identify various combinations	1995
[52]	analysis, case	of degree of individual factors	
	study	affecting TF	
Industrial applications of	Survey, case	Provide an intensive	1971
technological forecasting	study	examination of the	
[497]		organizational aspect in TF	

This research created online survey instrument using Qualtrics, as an online survey vendor, provided by Portland State University. The survey consisted of 16 questions about technology planning or technology forecasting activities in order to provide a more intensive investigation of the technological, methodological, organizational, and industrial aspects in which they are, or are not, found.

8.2.4. Step 2: Think Aloud

As a next step, this research conducted a "Think Aloud" session as a part of developing the survey questionnaire. The think aloud technique is typically used for usability test. The objective of the think aloud session is to read the survey



questionnaires aloud and improve, correct or modify the questionnaire as needed. A group of Ph.D. students from the department of Engineering and Technology

Management at PSU were recruited to take part in this process. Four Ph.D. students participated in this session, which took about 1.5 hours to complete. While they were going through the questionnaire, they were instructed to speak aloud and make a note of their thoughts and feelings with great attention to the wording and visual layout. They were also asked to fill out feedback form about their impressions with respect to each survey question. The valuable feedback from each participant was applied into the survey questionnaire, resulting in removing redundancy and filtering the survey element for improving response rate from companies. Total questions are reduced from 16Qs of initial survey to 14Qs of post survey of cognitive interview. Through this process, second version of the survey questionnaire was created by matching question wording to the concepts being measured and the population studied. The examples of feedback and modification are presented as follows:

Participant: "What is the meaning of each forecasting activity?"

Modification: Added definition of each forecasting activity to clarify survey items using hypertext function at Qualtrics.

Participant: "The question asks about what and when. The answer lists only about what is the purpose."

Modification: Modified the question to clarify intention of survey item.

Participant: "A little confused with the alternatives, i.e. Tech. Roadmapping is part of Tech. Planning and you also ask it in methodology questions."

Modification: Removed Tech. Roadmapping from answering lists.



8.2.5. Step 3: Pre-Validate

The second version of the survey questionnaire was tested in this process. The intention of this step was to develop and validate the preliminary web-based survey instrument. A group of Ph.D. students and colleagues who have experience in R&D, TF, or technology planning activities were invited to participate in this process. 26 colleagues and Ph.D. students participated in this step. They were asked to go through each survey question and give any feedback, comments, and suggestions that they might have in this survey questionnaire. The feesdback from each participant was reviewed and incorporated into the web-based survey questionnaire accordingly. The third version of the survey questionnaire was created. The example of feedback and modification is presented as follows:

Table 32 The example of pre-validation result

Second version	Modification for third version			Note			
Q3. Please indicate what is the purpose of technology forecasting in your organization. (Multiple		Q2. If your firm conducts technology forecasting for each of the following purposes, how do you rate the importance of technology forecasting performed by your planning staff(s) in your organization. (Multiple Choices)					Question number was
Choices)		Of no use	Not important	Moderate	Important	Extremely important	
As an aid in business planning and strategy	As an aid in business planning and strategy	0	0	0	0	0	corrected (from Q3 to
As an aid in R&D or technology planning	As an aid in R&D or technology planning	0	0	0	0	0	
As an aid in allocating resources	As an aid in allocating	0	0	0	0	0	Q2). They asked me to
As an aid in evaluating projects	As an aid in evaluating	0	0	0	0	0	
☐ To help justify a previously made decision	projects To help justify a previously		0	0	0	0	clarify the meaning of
To help in acquiring a government contract or subcontract	made decision To help in acquiring a						
To assess technology portfolios	government contract or subcontract	0	0	0	0	0	'redesign process.' They
☐ To redesign process	To assess technology portfolios	0	0	0	0	0	
To develop a new product or service	To redesign business or manufacturing process	0	0	0	0	0	recommended me to use
To identify new opportunities or threats	To develop a new product or service	0	0	0	0	0	T.1 . G 1
Others (please specify)	To identify new opportunities or threats	0	0	0	0	0	Likert Scale to get more
6	Others (Please, specify it)	0	0	0	0	0	specific informative data

8.2.6. Step 4: Expert Panel Validation

Expert panel was formed to assess and validate the third version of the survey questionnaire. They were asked to provide their feedback about this research on technology planning or technology forecasting within their firm. They were asked to evaluate each question with respect to intention of survey question, easiness of



answering a question, and other additional comments on each question. Invitation emails were sent to 6,563 experts and 79 experts agreed to participate as an expert panel. Finally, 37 experts involved in this step. This step took four weeks to complete. They were provided a link to web-based survey. Figure 13 presents the introduction page with instructions to the nature of this survey validation and what was expected.



Figure 13 Introduction letter of survey validation

The questions were presented to the expert panel one per page. For each question, this study provided expert panel with a textual definition of intention, along with background information. Expert panel were asked to answer three questions. First, they were asked to evaluate how the text of the question represents the intention of it on a scale of one to five. Second, evaluate how easy CEO, CTO, Vice President of Engineering, or General Manager answers to this question on a scale of one to five. Finally, they were asked to provide their feedback about anything missing from the text



or any additional opinion for each question. Figure 14 presents a screen shot of an example question and how these steps were implemented.

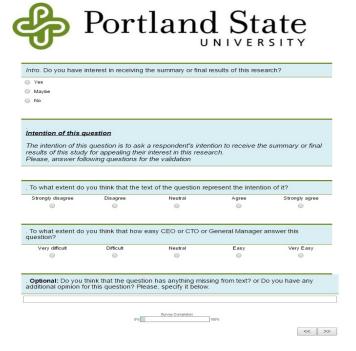


Figure 14 An example of online survey validation

• Intention; how well the question represents the intention of it, using a 5-point Likert scale:

1-Strongly Disagree 2-Disagree 3-Neutral 4-Agree 5-Strongly Agree

• Ease of answering; how easy respondents answer to this question, using a 5-point Likert scale:

1-Very Difficult......2-Difficult......3-Neutral.......4-Easy......5-Very Easy

The goal of this validation is to estimate the level of relevance and ease of answering in terms of each question. Achieving over four point scales for each evaluation would help demonstrate that each survey item is appropriately designed, well suited for the research question and objective, and easy to take this survey.



As presented in Table 33, the validation results safeguarded the rule of thumb, which is over four point scales. The mean of intention score was 4.27, and the mean of ease of answering was 4.17. To improve survey response, special care needs to be taken in ease of answering for Q4 (3.92), Q6 (3.9), Q7 (3.66), and Q8 (3.82).

Table 33 The results of expert validation

Overtion	Intention	Standard	Ease of Answering	Standard
Question	(Mean)	Dev.	(Mean)	Dev.
Introduction	4.50	0.69	4.55	0.69
Basic info.	4.31	0.73	4.34	0.75
Q1	4.41	0.60	4.33	0.66
Q2	4.44	0.55	4.36	0.67
Q3	4.34	0.63	4.37	0.59
Q4	4.18	0.64	3.92	1.06
Q5	4.29	0.65	4.27	0.84
Q6	4.05	0.92	3.9	1.05
Q7	4.08	0.81	3.66	1.24
Q8	4.11	0.84	3.82	1.14
Q9	4.24	0.68	4.23	0.78
Q10	4.35	0.54	4.32	0.70
Q11	4.22	0.59	4.35	0.63
Q12	4.35	0.68	4.32	0.88
Q13	4.24	0.76	4.03	1.08
Q14	4.21	0.70	4.0	1.04
Average	4.27		4.17	

Note: Intention Scoring Guidelines (1—Strongly disagree, 2—Disagree, 3—Neutral, 4—Agree, 5—Strongly agree), Easiness Scoring Guidelines (1—Very difficult, 2—Difficult, 3—Neutral, 4—Easy, 5—Very easy)

The expert panel responded additional comments on each question. Three to six experts proactively involved in questions and provided valuable feedbacks for each optional comment. A sample of notes from expert panel is as follows:

• Introduction:

- Three letter acronyms should always be defined, no matter how simple they are.



- Engineering and Technology is a very broad term. If the target of this survey is for industrial operations, I would tend to go to the VP or Director of Engineering and/or R&D. I don't know that the gift cards are of any particular value or need.

• Basic information:

- The number of employees is often not public information and cannot be disclosed by employees.
- Do you really need all this from all respondents? Respondents sometimes wish to remain anonymous and are wary of providing email addresses.

• Question 2:

- One thing I don't know what "To redesign process" means. Does it mean to change the fabrication process by which a product is built or a service is supported? Does it mean to change processes by which products are designed? Does it mean to change business processes within the company? Does it mean to change how technologies are forecast? All of the above? This entry needs to be more specific.
- Fairly difficult question as many answers may apply. But a good question.
- Question 5:
- Missing are technology journals, magazines, newsletters.
- Most organizations use a complex mix of sources; I'm not sure if this is useful.
- Question 8:



- Many techniques have multiple names. A glossary is needed. Methods have different purposes in technology forecasting- again I think you need to focus on a narrower purpose for this survey to be useful.
- Maybe a hyperlink to a definition for each term?

8.2.7. Step 5: Pilot Test

After consolidating expert panel's feedback with respect to relevance and ease of answering and additional clarifications, fourth version of the survey questionnaire was incorporated into a web-based survey instrument. The invitation emails were sent to a total 79 expert panel members who are the subset of potential respondents such as CEO, CTO, Vice President of Engineering, and Senior Managers of firms in manufacturing sectors, which range from 20 to 39 based on the two digit code of standard industrial classification (SIC) and 8711 code. They were asked to answer each question in the actual respondent position. A pilot test with 79 experts was performed before the final survey was sent out to actual respondents in order to ensure that the measurement errors were removed. Finally, this study collected 32 valid responses and the final version of the survey instrument was established. Specifically, the survey data includes such variables as the total number of employees, the ratio of R&D investment, sales revenues, etc. This research also gathered the total number of patents granted of each firm from second-hand objective data sourced from USPTO and WIPO. The patents examined in this research include utility and invention patents since design patents generally have no association with technological changes. I measured R&D performance by employing the number of all patents granted in a particular year on the basis of recent five-year window.





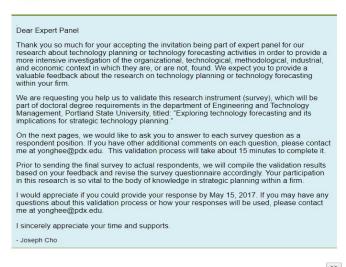


Figure 15 Introduction letter of pilot test

8.3. Survey Administration

8.3.1. Targeted Population

The unit of analysis in this study is "a firm" and the key informant is a CEO, CTO, Vice President of Engineering, or General Manager who is involved in strategic planning, technology planning, or technology forecasting of R&D projects from each company. The rational scope described in the next section presents U.S.-based manufacturing and engineering service companies that involves in R&D activity as the population of interest.

8.3.2. Sampling Frame

This study attempts to select a sample that is representative of the relevant population. This research utilizes ReferenceUSA and LexisNexis database as a university accessible database to obtain the list of manufacturing and engineering



service firms in the U.S. One can search a firm with a wealth of individual criteria such as company name, SIC or NAICS description, geography, category, size, revenue, annual sales volume, total assets, gross profit, earnings per share (EPS), job titles, name, gender, website, email, phone number, fax number, and etc.

The focus of this research is on SIC codes from 20 to 39, and 8711, which mainly describe manufacturing and engineering service industries. Based on this database, industry code, job titles, and geography are the criteria to select companies. If a firm has multiple people to be targeted, a single contact is retained. Finally, single contact information per a firm was used for this survey. The List in manufacturing directory has email contact information of 6,563 companies. At the validation stage, 437 emails were identified as no longer active, available or invalid emails.

Consequently, 6,000 out of 6,126 firms were randomly selected to be reached from this database for the survey.

8.3.3. Sample Size

A number of simulation studies have been conducted to investigate the effects on SEM fit indexes of sample size. In addition, there are many issues to take into account with respect to minimum sample sizes. Minimum sample size is recommended based on having sufficient sample size to reduce the likelihood of convergence issues and to obtain unbiased estimates or standard errors. Based on simulation studies, which indicate an unacceptable number of models failed to converge when the sample size was 50, Anderson and Gerbing suggested 100 minimum sample sizes [498]. For analyses with fewer than 100 or so cases, some researchers would suggest using t critical values instead of z critical values for parameter significance tests. After



reviewing previous studies regarding sample size and goodness-of-fit issue in SEM, Tanaka proposed a maximum entropy measurement error (ME2) estimation as an alternative solution to the small sample size [499]. Ad hoc rules of thumb given for statistical models would be 10:1 subjects-to-parameters ratio for arbitrary distribution [500]. The optimal ratio of subject to free parameters is unclear, however. Although the 10:1 ratio is often considered safe, simulation work by Nevitt and Hancock propose that there are some conditions when this is not sufficient [501]. Jackson identified the improvement of GFI, γ2 goodness-of-fit index bias, and the RMSEA, when sample size reaches 200 to 400 [502]. Yu pointed out that overcorrection of standard errors can occur if sample sizes are smaller than 250 under moderate non-normality [503]. Another approach to dealing with nonnormality in SEM is bootstrap resampling, which requires over 200 bootstrap samples in the simulation [504]. However, performance may depend on the complexity of the model. Savalei and Bentler recommend the direct maximum likelihood (ML) method with appropriate corrections as a reliable approach to handling incomplete nonnormal data [504].

In summary, presented in table 34 are recommendations commonly noted in the literature with respect to the minimum sample size. These recommendations, however, should not be taken as definitive, infallible, or exact, because simulation studies can only examine a few conditions at a time and often involve simplified conditions compared with actual practice. Therefore, there has been increased demand for methods that perform optimally at smaller sample sizes and under varied distributional conditions [501].



Table 34 Minimum sample size recommendations

Estimator Maximum Likelihood (ML) with multivariate	Recommended Minimum N > 100 200-400	References [498] [502]	Notes These recommended sample sizes are based
normal data	5:1 ratio of cases	[499][500]	on ML estimation with
	to free parameters		multivariate normal
		[500]	data, which may be
	10:1 ratio of cases		somewhat rare in
	to free parameters		practice, and correctly
			specified models
MLM (ML with robust		[505][503]	When data are
standard errors and			multivariate normal,
scaled chi-square), for	> 250		standard ML and
nonnormal continuous			MLM will have the
variables			same estimates
Bootstrap, for		[504]	They note that a sample
nonnormal continuous	200-1000		size of 100 could be
variables	200 1000		sufficient for simple
			models
MLR (robust ML), for		[506]	This recommended
continuous nonnormal			sample sizes is based
missing data	> 400		on percentage of
			missing data. (e.g. 30%
			missing)
Robust DWLS with		[507]	500 or more samples
polychoric correlations,			may be need for
with binary ordinal	200-500		sufficient power to
variables (WLSMV in			reject models. Less
Mplus and lavaan)			than 200 seem to be



	associated with serious
	standard error bias

Source: adapted and modified from [466]

Based on various scenarios of response rate as well as recommendations in the literature, the minimum effective sample sizes for this research are simulated as follows. The initial model of this research consists of eight factors and 12 indicators. Sample size conditions reflect subject-to-estimated parameter ratios and recommended minimum sample size. (See table 35)

Table 35 Scenarios of properly specified sample sizes

Scenarios of expected	Model estimator	Number of factors of		Minimum sample size conditions			Targeted sampling
response rate (%)	estillator	of factors	indicators	5:1	10:1	> 200	space (N)
5%		8	11	130	260	200	4,000
6% 7%	ML with multivariate	8	11 11	130 130	260 260	200 200	3,333 2,857
8%	normal data	8	11	130	260	200	2,500
9%		8	11	130	260	200	2,222
10%		8	11	130	260	200	2,000

Sufficient power to reject a model based on the chi-square test of the model is another significant subject. Hu and Bentler examined how alternative fit indices perform with different sample sizes [505]. The assessment of model fit in SEM depends on the probability level of the chi-square value, which examine the discrepancy between the original sample covariance matrix and the reproduced covariance matrix based on the model specifications [508]. When sample size is large, the assessment of model fit would be stringent. The statistical test, however, is lenient, when sample size is small.



Normally, sample size has an increasing effect on chi-square values. Models with more variables tend to have larger chi-squares. Absolute fit indices (e.g., chi-square, RMSEA) appear to be more sensitive to misspecification than relative fit indices (e.g., CFI).

To supplement the chi-square estimate, a variety of fit indexes have been developed to assess different criteria under different theoretical rationales. (See Table 36) Tanaka divided fit index into six dimensions to justify the use of fix indices [509]. Although there are many contradictory claims over the ideal use of diverse fit indexes, the following fit indices are normally considered: Comparative Fit Index (CFI), Bollen's Incremental Fit Index (IFI), Tucker-Lewis Index (TLI) and the Root Mean Square Error of Approximation (RMSEA). Bentler introduced the comparative fit index (CFI) based on the noncentrality parameters [510]. Bollen developed new incremental fit index (IFI), which adjusts the normed fit index for sample size and for the degrees of freedom of the maintained model [511]. Both IFI and TLI fall into relative fit indices, which compare a chi-square for the model tested to one from a so-called null model. TLI and IFI are relatively unaffected by sample size [512][513].

$$TLI = \frac{\left(d_0 / df_0\right) - \left(d_{model} / df_{model}\right)}{d_0 / df_0}$$

Where d_{model} and df_{model} are the noncentrality parameter and the degrees of freedom for the model tested and d_0 and df_0 are the noncentrality parameter for the null model. In addition, RMSEA proposed by Steiger and Lind[514], a noncentrality-based index, is based on a test that the null hypothesis is true (χ^2 =0). RMSEA represents that how well the model, with unknown but optimally chosen parameter estimates, would fit the population covariance matrix [515]. RMSEA is less preferable when sample size is



small, because it has a tendency to overreject true-population models at small sample size [505]. Most of these fit indices are computed by using ratios of the model chisquare and the null model chi-square taking into account their degrees of freedom. An earlier convention used above .90 as a cutoff for good fitting models. Hu and Bentler, however, suggest that there seems to be some consensus now that this value should be increased to approximately .95 [505]. Hu and Bentler in their study empirically examine various cutoffs for many of these measures, and their data suggest that researchers should use a combination of one of the relative fit indexes and the SRMR, in order to minimize Type I and Type II errors under various conditions [505].

Missing data as same as given dataset is a pervasive problem in the social sciences. Unfortunately, dropping incomplete cases results in sacrificing information from the sample and can lead to biased estimates when the data is not missing completely at random. In recent years, probably the most pragmatic missing data estimation approach for structural equation modeling is full information maximum likelihood (FIML), which has been shown to produce unbiased parameter estimates and standard errors under MAR and MCAR. Just "ML," is currently available in all major SEM packages. In this analysis, this study also used FIML to deal with missing value as well.



Table 36 Cutoff criteria for several fit indexes

Absolute/predictive fit		General rule for fit (continuous data)	data
Chi-square	χ²	Ratio of χ^2 to df ≤ 2 or 3, useful for nested models/model trimming	
Akaike information criterion	AIC	Smaller the better; good for model comparison (nonnested), not a single model	
Browne–Cudeck criterion	BCC	Smaller the better; good for model comparison, not a single model	
Bayes information criterion	BIC	Smaller the better; good for model comparison (nonnested), not a single model	
Consistent AIC	CAIC	Smaller the better; good for model comparison (nonnested), not a single model	
Expected cross- validation index	ECVI	Smaller the better; good for model comparison (nonnested), not a single model	
Comparative fit			
Normed fit index	NFI	≥ .95 for acceptance	
Incremental fit index	IFI	≥ .95 for acceptance	
Tucker-Lewis index	TLI	\geq .95 can be $0 > TLI > 1$ for acceptance	0.96
Comparative fit index	CFI	≥ .95 for acceptance	0.95
Relative noncentrality fit index	RNI	≥ .95, similar to CFI but can be negative, therefore CFI better choice	
Parsimonious fit			
Parsimony-adjusted NFI	PNFI	Very sensitive to model size	
Parsimony-adjusted CFI	PCFI	Sensitive to model size	
Parsimony-adjusted GFI	PGFI	Closer to 1 the better, though typically lower than other indexes and sensitive to model size	
Other			
Goodness-of-fit index	GFI	≥ .95 Not generally recommended	
Adjusted GFI	AGFI	≥ .95 Performance poor in simulation studies	
Hoelter .05 index		Critical N largest sample size for accepting that model is correct	
Hoelter .01 index		Hoelter suggestion, N = 200, better for satisfactory fit	
Root mean square residual	RMR	Smaller, the better; 0 indicates perfect fit	
Standardized RMR	SRMR	≤ .08	
Weighted root mean residual	WRMR	< .90	< .90
Root mean square error of approximation	RMSEA	< .06 to .08 with confidence interval	< .06

Source: [516]



8.3.4. Sampling Method

Sampling methods can be divided as either probability or nonprobability [517]. In probability samples, each population element has a known non-zero chance of being selected for the sample. Probability methods include random sampling, systematic sampling, stratified sampling and cluster sampling [480]. The advantage of probability sampling is that sampling error can be identified. Sampling error is the extent to which a sample might differ from the population [472]. Sampling error depends on sample size. In nonprobability sampling, the extent to which the sample differs from the population remains unknown.

For this research, simple random sampling tool is used to determine the targeted samples. Simple random sampling is that members of the subset are chosen completely at random so that every member of the population has an equal probability of being selected. Systematic sampling is a versatile form of random sampling [480]. After the required sample size has been computed, every Nth element is chosen from the population. If the list does not include any hidden order, this sampling method is as good as the random sampling. The advantage of systematic sampling over the random sampling is flexibility and simplicity [480]. Stratified Sample is that the population is divided up into relatively homogeneous groups [518]. A stratum is a subset of the population that shares at least one common characteristic. A proportionate sample is drawn from the groups. Cluster sampling is employed when natural but homogeneous groupings are evident in a population. So, the total population is divided into clusters and random sample is drawn from each natural grouping.



8.3.5. Sampling Administration

After the survey design had been finalized, the survey invitation emails were sent out to randomly chosen 6,000 firms with four follow-ups, following 14 parts of Dillman's guidelines as presented in Figure 11. The initial round of survey invitations were sent during the first week of June 2017. Typically, follow-ups after sending a self-administered questionnaire increase response rates [480]. In this research, four follow-ups were conducted to improve response rates. All subsequent follow-up emails were sent out to only non-respondents, so that respondents do not receive additional requests to take the survey, emphasizing the significance of their response as well as highlighting some incentives to improve response rate [519][480]. All follow-up emails also stressed that the survey would take a short amount of time (10-min) to complete.

Contact timing is important. However, the optimal timing sequence for web-based surveys varies based on the objectives and targeted population [472]. In this research, follow-up contacts were sent in about two weeks' interval for giving adequate time to respond since most management group tends to be out of office for business trips. In this study, the initial survey invitations and four follow-ups were sent out to respondents. Consistent with prior research [472], second follow-up yielded significant gains in this study. Figure 16 illustrates survey responses over time, which takes three months to collect enough responses for the SEM analysis in this research. At the conclusion of data collection, 87 non-engaged responses had been identified and removed, finally 253 responses were usable.



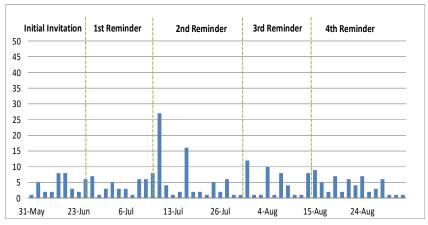


Figure 16 Survey responses over time

8.3.6. Response Rate (RR)

Due to increase of mistrust, a sense of being "over-surveyed," and the proliferation of "sugging," the response rate of the survey has been declined [520][480]. The response rate varies widely depending on the goals and needs of the study, survey mode, targeted population, and sampling frame. Reported response rates to mail surveys differ considerably ranging from 2.5% to 97.7% [521]. Kaplowitz *et al.* indicated that the response rate to the mail is typically larger than the web-only [481].

As illustrated in Figure 11 in this chapter, following Dillman's design technique, some measures were taken to increase response rate as follows:

- Trust: Portland State sponsorship in the email headline and survey instrument
 design, emphasizing their significant contribution to the body of literature,
 personalizing the emails with first and last name, and responding quickly to all
 participants' inquiries.
- Rewards: offering the summary of the results at the introduction page, and monetary incentives.
- Ensure anonymity and confidentiality.



• Four follow-ups to increase response rate.

The response rate for this survey is as follows:

Initial invitation:
$$RR = \frac{37}{6,000} = 0.62\%$$

First reminder:
$$RR = \frac{35}{5,963} = 0.59\%$$

Second reminder: RR =
$$\frac{77}{5,928}$$
 = 1.3%

Third reminder: RR =
$$\frac{40}{5.851}$$
 = 0.68%

Fourth reminder: RR =
$$\frac{64}{5,451}$$
 = 1.17%

Total:
$$RR = \frac{253}{6000} = 4.22\%$$

In this research, consistent with the expectation of prior research [472], the response rate (4.22%) of web-only survey seemed to be low. As presented in Table 37, a typical response rate of Ph.D. dissertations ranges about 2~13%. However, low response rate simply do not necessarily indicate bias or problem [522][472]. On the other hand, higher response rates do not necessarily mean that nonresponse error is reduced [523]. Respondent characteristics are representative of non-respondents. In SEM research, several studies have suggested various minimum sample sizes, ranging from roughly 50 [524] to 250 [505][503] based on estimators as described in Table 34. Prior research indicated that 200 or more responses would be satisfactory for complex models [525]. Consequently, the sample size in this research is within the expected and acceptable range.

Table 37 Prior Ph.D. dissertations and response rate

Title	Sample size	Responses	RR (%)
Technology evaluation and acquisition strategies and their implications in the U.S. electronics manufacturing industry [526]	1,987 U.Sbased electronics manufacturing firms	226	11.4
Supply chain integration practices in the U.S. electronics industry [527]	1,917 US Electronics firms in the U.S.	99	5.16
Supply chain orientation: Refining a nascent construct [528]	13,705 Manufacturing firms in Canada	227	1.65
Examining health information technology implementations: Case of the patient-centered medical home [529]	1,820 clinics in the U.S.	146	8
Exploring capability maturity models and relevant practices as solutions addressing IT service offshoring project issues [530]	9,030 IT and Software developing firms in the U.S.	551	6.1
Exploratory study of the adoption and use of the Smartphone technology in emerging regions: Case of Saudi Arabia [531]	5,000 Smartphone users in Saudi Arabia	657	13.14

8.3.7. Respondent Profile

The completed surveys demonstrated that typical respondents could be described as senior managers of engineering who had experienced in new product development, strategic planning, technology planning, and forecasting activities before. As presented in Figure 17, a total of 121 (47.8%) respondents identified themselves as a director in their firms. The respondents' average of experience in industry was 27 years (S.D. = 8.7 yrs).

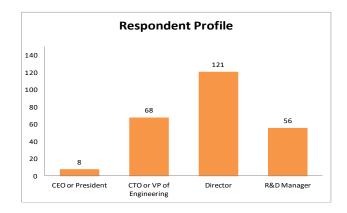




Figure 17 Respondent's position

They could have applied one or more TF techniques when involving in their R&D projects. The firms they represent could be described as all sizes of U.S.-based manufacturing companies that engage in R&D. A total of 128 (50.6%) were identified as large firms based on small business size standards matched to North American Industry Classification System (NAICS) codes by U. S. Small Business Administration (SBA) [532]. As shown in Figure 18, SIC 36 electronics (52, 20.6%), SIC 35 computer equipment (50, 19.8%), and SIC 38 analyzing instruments (38, 15%) are the top three most frequent responses by sector in this survey.

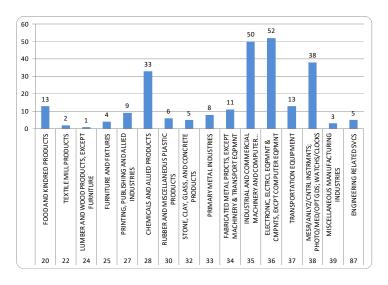


Figure 18 Respondents by industry

8.3.8. Nonresponse Error; Wave Analysis

Extrapolation approach of time trends was used to test non-response error [533][523][522]. It assumes that non-respondents would be similar to the individuals who responded later in the administration period. Analysis of variance (ANOVA) was performed to examine the possibility of absence of response bias. The results revealed



that there were no significant differences between respondents among the four follow-ups, compared based on variables—firm size, TF activities, technology planning, return on assets (ROA), earnings growth, sales growth, and other variables measured in this survey. Thus, the results indicated that there was no evidence of non-response bias.

Table 38 The results of wave analysis

Variable	es	Sum of Squares	df	Mean Square	F	p
T 1 1 C +:	Between Groups	1.349	4	0.337	0.282	0.890
Technology forecasting	Within Groups	272.900	228	1.197		
(three to five years)	Total	274.249	232			
T. 1 1 C	Between Groups	5.390	4	1.348	0.991	0.413
Technology forecasting (over five years)	Within Groups	310.001	228	1.360		
(over five years)	Total	315.391	232			
	Between Groups	1.697	4	0.424	0.426	0.790
Technology planning	Within Groups	229.324	230	0.997		
	Total	231.021	234			
Multiple use of TF	Between Groups	.361	4	0.090	0.156	0.960
methods	Within Groups	108.975	188	.580		
methods	Total	109.337	192			
Satisfaction with the	Between Groups	12.300	4	3.075	1.343	0.256
results of TF	Within Groups	435.187	190	2.290		
results of 11	Total	447.487	194			
The usefulness of TF on	Between Groups	3.643	4	0.911	0.439	0.780
technology planning	Within Groups	390.109	188	2.075		
technology planning	Total	393.751	192			
R&D Fundamental or	Between Groups	26.843	4	6.711	1.875	0.117
basic research	Within Groups	654.875	183	3.579		
basic research	Total	681.718	187			
	Between Groups	38.080	4	9.520	1.859	0.120
R&D Applied research	Within Groups	932.016	182	5.121		
	Total	970.096	186			
	Between Groups	35.931	4	8.983	1.248	0.292
R&D Development	Within Groups	1324.735	184	7.200		
	Total	1360.667	188			
Sales growth	Between Groups	14.017	4	3.504	1.990	0.098
	Within Groups	318.720	181	1.761		
	Total	332.737	185			
Return on assets (ROA)	Between Groups	12.104	4	3.026	2.072	0.087
	Within Groups	249.691	171	1.460		
	Total	261.795	175			
	Between Groups	6.844	4	1.711	1.074	0.371
Earnings growth	Within Groups	283.462	178	1.592		
	Total	290.306	182			



8.3.9. Nonresponse Error; Item Nonresponse

In Qualtrics system, 87 non-engaged respondents who did not answer any questions were identified and removed. The survey questions were designed for participants to skip or move to the next question before they select an answer to each question. Thus, there were some of incomplete or missing data in the surveys that were employed in the analysis for this study. Missing measurement items were presented in Table 39.

Table 39 Missing measurement items by each survey question

Question	Validation Type	# of Records	Missing	% of Total
Basic info.	Validated optional	253	0	0
Q1	optional	235	18	7.1
Q2	optional	219	34	13.4
Q3	optional	211	42	16.6
Q4	optional	200	53	20.9
Q5	optional	197	56	22.1
Q6	optional	188	65	25.7
Q7	optional	201	52	20.6
Q8	optional	184	69	27.3
Q9	optional	193	60	23.7
Q10	optional	195	58	22.9
Q11	optional	193	60	23.7
Q12	optional	194	59	23.3
Q13	optional	189	64	25.3
Q14	optional	186	67	26.5

8.3.10. Post-survey Adjustments and Missing Data

After data have been collected, post-survey adjustments can be conducted to address survey nonresponse. However, the extensive efforts such as additional call or interview attempts and refusal conversion protocols have been realistically ineffective and costly [534]. In this regard, several weighting techniques [535][536] can be one of the post-survey adjustment methods. However, unfortunately, it is difficult to identify available variables that are highly correlated with both participation propensity and with



the survey outcome variable of interest for nonresponse adjustment [537]. Typically, geographic and demographic variables can be used in post-survey adjustments, but those variables cannot be applied to this research.

On the other hand, nonresponse items are typically regarded as either missing at random (MAR) or being systematic. According to prior research [538], the missing data mechanism in this sample can be considered as MAR, so other adjustment methods are not needed to reduce nonresponse bias. Thus, there are several techniques to deal with missing data relevant to the hypotheses. Listwise deletion has been the most common way of dealing with missing data in structural equation model. In recent years, however, researchers have begun to employ data estimation tools—maximum likelihood (ML)/full information maximum likelihood (FIML), expectation maximization algorithm (EM), and Bayesian multiple imputation (MI)—for dealing with missing data in SEM [539]. Consequently, this research used FIML to deal with missing data issue.

8.3.11. Reliability

This study employs Chronbach's alpha to examine for internal consistency and reliability of the scale items in the hypothesized model. Cronbach alpha coefficient was computed for each variable as presented in Table 40. A Chronbach's alpha coefficient of greater than 0.7 indicated that the factors have an acceptable level of internal consistency and reliability of the survey-based constructs.

Table 40 Reliability test results

Factor	Number of items	Chronbach's Alpha	Specifications
Appropriate use of TF	2	.982	Reflective
The use of TF	2	.826	Reflective
Business performance	3	.807	Reflective



Chapter 9 Analysis

9.1. Construction of Measures

Measures of the use of TF techniques, the effectiveness of TF activities, TF activities, technology planning, R&D performance, and business performance were used in this research. Multi-item indicators used in the survey were developed and adopted through a review of prior research. Existing measurement scales were identified from the literature. This study adjusted these measurement scales to fit the variables.

Technology forecasting

TF consists of subset elements such as a certain future time span, technological change, continuous range of characteristics in applications, and a statement of the probability associated with the technology [32]. It is important to note that determining appropriate TF methods is critical for a given situation in order to forecast proper technological changes, since the methods employed inevitably affect TF results [23][49]. Furthermore, several studies indicated that the type of R&D such as basic research, exploratory research, applied research, development, and product improvement influences measurement techniques and the metrics [288][341][421]. The choice of TF methods might depend on the type of R&D such as basic research, applied research, and commercialization [26]. Furthermore, the selection of proper TF tools depends on the nature of the technologies [26]. The relevance and availability of data and the appropriate selection of TF techniques are basic elements to improve the effectiveness of the forecast in strategic technology planning [49][415].



To measure the use of TF, two items were developed. For the appropriate use of sophisticated TF practices, 28 items were measured and standardized before conducting the analysis.

Variable 1: the use of TF. This variable represents the firm's commitment to TF. It also showed a firm's aggressive use of TF in developing new products/processes/technologies. Two items were created to measure short-term and long-term TF activities in a firm. This variable captures the breadth of the firm's use of TF associated with technology characteristics. The respondents were asked to indicate on five-point Likert-type scales the extent to which each measure characterizes a firm's TF activities. A high score on this variable indicates a strong commitment to TF. This scale has a mean of 3.19 and a standard deviation of 0.19 ($\alpha = 0.82$).

Variable 2: the appropriate use of TF. This variable captured the breadth of the firm's use of TF associated with technology characteristics—continuous and discontinuous technology. It also indicated its strong commitment to TF. A high score on this indicated that the firm properly uses TF methods based on technology characteristics and showed intensive commitment to TF.

Technology characteristics

Several studies indicated that the type of R&D—basic research, exploratory research, applied research, development, and product improvement—influences measurement techniques and the metrics [296][349][429]. Hauser [540] divided innovation activity into three stages—basic research, development, and applied engineering, while Leifer and Triscari [541] into research and development. Werner and Souder [542] classified R&D into four types: basic research, applied research, product



development, and manufacturing process R&D. Organization for Economic Cooperation and Development (OECD) organized R&D into three types of activity—basic research, applied research, and experimental development [543]. Although there seems lack of clear-cut classification, they all characterize the focal points of unstructured R&D activities. Following the lead of OECD, this research divides technology into three categories: basic research, applied research, and development. Table 41 presents the characteristics of each R&D.

Table 41 Technology characteristics

Technology characteristics	Description
Basic research	Experimental or theoretical work undertaken primarily to acquire knowledge related to disruptive product/process or service
Applied research	Original investigation undertaken to acquire knowledge directly related to next generation product/process or service
Development	Systematic work or practical research for new applications/discoveries related to the current product/process or service

TF resources

To measure internal/external TF resources, two items were developed respectively. 13 indicators of each item were measured before conducting the analysis. The respondents were asked to indicate on five-point Likert-type scales the extent to which each measure characterizes the use of internal/external resources. A high score on this variable shows the extent to which the firm devotes internal/external resources to TF activities. This scale has a mean of 2.54, and a standard deviation of 0.16 (α = 0.91)

R&D performance

As summarized in Table 22, there have been a variety of indexes to measure R&D performance by patents—total number of patents filed or granted, and the total



number of patent citations. The most common output indicator is a patent such as the number of patents granted that is used in this research.

Business Performance

In this study, the measurement of business performance is based on outcome indicators rather than outputs or impact indicators, because the data should convey the economic sense. This study found that there is no significant trend favoring a single measure of a firm's business performance. In this regard, this study identifies that sales growth, ROA, earnings, and market share are the most extensively used to measure business performance in the literature as described in Table 23. This study initially considers sales growth, ROA, earnings growth, and market share changes for the previous five-year period as indicators of a firm's business performance in order to examine the association between technology planning, R&D and business performance. Consequently, based on the results of confirmatory factor analysis, this research used a firm's five-year average changes in sales growth, earnings growth, and ROA to measure its business performance.

9.2. Confirmatory Factor Analysis (CFA)

To assess the unidimensionality of the survey-based constructs, this research used confirmatory factor analysis. Moreover, to answer to the hypothesis, Pearson's correlation, CFA, and structural equation modeling (SEM) are employed to investigate not only relationship between TF activities and technology characteristics but also causal relationship among variables, and finally statistically test hypotheses proposed in Figure 3, based on the literature review. SEM is an appropriate tool to analyze path



model with latent variables in order to uncover causal structures. The hypothesized relationships in this model have multiple intercorrelations between a set of variables, which are developed based on literature review and hypothetical assumptions. A straight, one-headed arrow represents a causal association between two variables. This model cannot be solved by ordinary least squares (OLS) regression techniques. Multiple regression can be regarded a special case of SEM [453]. By contrast, SEM approach is a multivariate tool that takes into account complete and simultaneous equation of all relationship in a given model. SEM approach allows us to easily articulate relationships of all variables with one another [454]. This research focuses on the causal inference in latent variable models. The causal relationship is the focal point of SEM analysis [453]. Path model incepted in population genetics to model inheritance by Sewall Wright in 1918 [455] and later widely applied to various situations in psychology and sociology [456]. Path models and multiple regression provide the core information needed to understand the broad class of SEM [454]. Path analysis gauges the strength of causal relations among variables in multiple systems of equations based on the correlation matrix of observed variables [457]. In the 1970s cross-disciplinary integration ended up with structural equation modeling. SEM mainly deals with the specification of causal relations among variables. Path modeling is integrated with the logic of factor analysis [454]. Based on the groundwork Karl Pearson and Charles Spearman made in the 1900s, factor analysis was developed to explore the structure of intelligence in multivariate data [462]. Factor analysis has been widely used for the analysis of correlated data [463]. Factor analysis is designed to link factors to measures that are defined in terms of weights [454]. CFA requires the specification of particular factor



structure, whereas exploratory factor analysis (EFA) allows all items to load on all factors [466]. CFA approach attempts to examine whether or not observed data are consistent with the posited theoretical model. CFA provides a chi-square test and goodness-of-fit indicators.

CFA with full information maximum likelihood using SPSS Amos 22 was performed to establish the measurement of the constructs in the model. A major component of a CFA is to test the reliability of the observed variables [516]. Initial measure items were constructed based on the knowledge and empirical research through the literature review. In terms of business performance measure, market share was ruled out, since it resulted in an unsatisfactory model fit. Consequently, three accountingbased indicators such as ROA, earnings growth, and sales growth are loaded for measuring business performance. The chi-square value was insignificant, $\chi^2(11) =$ 12.167, p = 0.35, indicating good fit to the data [544]. Alternative fit indices were also examined to decide whether the model fit was adequate. Alternative fit indices indicated acceptable fit, Comparative Fit Index (CFI) = .998, Bollen's Incremental Fit Index (IFI) = .998, Tucker-Lewis Index (TLI) = .995, Root Mean Square Error of Approximation (RMSEA) = 0.028. All measure items loaded significantly on their intended constructs, demonstrating convergent validity. All results of CFA are presented in Table 42. In addition, the Cronbach's alpha coefficient over 0.70 is considered an adequate level of internal consistency estimate [545]. Cronbach's alpha of all three latent variables (The use of TF (0.83), Business performance (0.81), and Appropriate use of TF (0.98)) was the acceptable level of reliability.



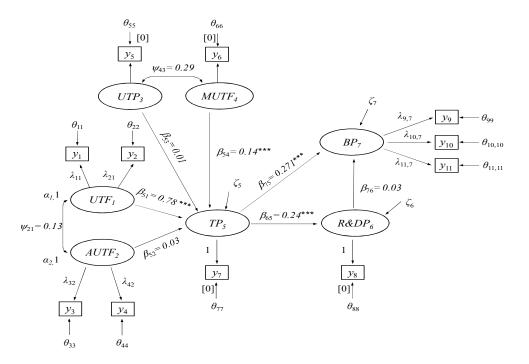
Table 42 The output of three factor loadings

Observed variables	Latent	Standardized	S.E.
Observed variables	construct	Loading	S.E.
	The use of TF		
	(UTF)		
• TF activity (three to five years)		0.74	0.093
• TF activity (over five years)		0.93	0.098
	Business		
	Performance		
	(BP)		
• Changes - Return on Assets (ROA)		0.82	0.108
Changes - Earnings growth		0.93	0.112
Changes - Sales growth		0.78	0.115
	Appropriate		İ
	use of TF		
	(AUTF)		
Appropriate TF use for discontinuous tech		0.89	2.370
Appropriate TF use for continuous tech		0.91	2.298

9.3. Full Structural Equation Model

The graphic representation illustrated in Figure 19 is the hypothesized model that was tested to see how TF activities affect technology planning, R&D performance, and the business performance. SEM analysis was conducted to measure hypothesized associations among model constructs with full information maximum likelihood (FIML). The structural equation model (SEM) in Figure 19 presents the relationships among latent constructs and observable variables as a succession of seven structural equations. SEM technique, as implemented by SPSS AMOS 22, was used for data analyses.





Note: The Use of TF (UTF), The Appropriate Use of TF (AUTF), The Usefulness of TF in TP (UTP), The Multiple Use of TF (MUTF), Technology Planning Activity (TP), R&D Performance (R&DP), Business Performance (BP)

Figure 19 Full structural equation model with the results

The following fit indices were considered: CFI, IFI, TLI and RMSEA. Most of these fit indices are computed by using ratios of the model chi-square and the null model chi-square considering their degrees of freedom. As described in detail in Table 43, this research used above .95 as a cutoff for good fitting models, as Hu & Bentler suggest that there seems to be some consensus now that this value should be increased to approximately .95 [544]. As shown in Table 43, alternative fit indices suggested highly acceptable fit of full structural equation model. The model presented variance and covariance between factors with good fit indicators.



Table 43 Goodness of fit indices for full structural equation model

Index	Threshold	Value
CFI	≥ .95 for acceptance	0.989
IFI	≥ .95 for acceptance	0.989
TLI	≥ .95 for acceptance	0.978
RMSEA	< .06 to .08 with confidence interval	0.052

Description Measurement scale

The Use of TF (UTF) 1-No use

2-Not often conducted

3-Somewhat often conducted

4-Often conducted

5-Very often conducted

The Usefulness of TF in TP (UTP) 1-Very negative

2-Negative

3-Somewhat negative

4-Neutral

5-Somewhat positive

6-Positive

7-Very positive

The Multiple Use of TF (MUTF) 1-No

2-Do not know

3-Yes

Technology Planning Activity (TP) 1-No use

2-Not often conducted

3-Somewhat often conducted

4-Often conducted

5-Very often conducted

R&D Performance (R&DP) The number of patent granted ('12-'16)

Business Performance (BP) 1-Less than -30%

2- -10 to -20%

3- Larger than equal to -10%

4-0

5-Less than equal to 10%

6-10 to 20%

7-Over 30%



Chapter 10 Results

10.1. The Importance of TF

TF methods have been used for various purposes as discussed in chapter 1. Thus, the respondents were asked to rate how they have used TF techniques for following objectives. As presented Table 44, the results confirm that TF plays a crucial role to identify potential areas for research or new business in many firms in strategic planning and assessing processes. Developing a new product or service, aiding in R&D planning and identifying new opportunities and threats are the top three most frequent responses in this survey.

Table 44 The importance of TF in each activity

The purpose of TF	N	Mean	Std. Deviation
To develop a new product or service	219	4.087	0.8866
As an aid in R&D or technology planning	216	4.060	0.9406
To identify new opportunities or threats	219	4.037	0.9426
As an aid in business planning and strategy	218	3.890	0.9391
As an aid in evaluating projects	217	3.664	0.8290
As an aid in allocating resources	219	3.648	0.8724
To redesign business or manufacturing process	219	3.306	1.0148
To assess technology portfolios	217	3.143	1.1558
To help justify a previously made decision	219	2.868	0.9935
To help in acquiring a government (sub)contract	215	2.284	1.1635

Note: the mean is the average on a scale of 1 (of no use) to 5 (extremely important)

10.2. Planning Activities

There are various planning activities conducted not only to establish a various type of strategic plans in companies but also to identify opportunities or risks that they face. Thus, to capture the intensity of planning activities in firms, participants were asked to answer how often they have used each planning activity in their organization. As



shown in Table 45, most companies involve in short-term planning activities such as annual planning, short-term forecasting, and action planning.

Table 45 Responses to planning activities

Planning activity	No use	Not often	Somewhat often	Often	Very often	Mean	Std. Deviation
Annual Planning	4	9	17	62	139	4.398	0.9121
Short-term Forecasting (less than one year)	6	16	30	56	122	4.183	1.0703
Action Planning or Operational Planning (one to three years)	4	13	36	85	93	4.082	0.9678
Strategic Planning (3 to 5 years)	4	25	47	74	78	3.864	1.0636
Market Forecasting	10	25	43	85	70	3.773	1.1199
Technology Planning	3	22	73	76	61	3.723	0.9936
Technology Forecasting (3 to 5years)	6	41	66	71	49	3.498	1.0872
Technology Forecasting (over 5 years)	20	85	61	38	29	2.876	1.1660
Long-range Planning (over 5 years)	19	56	65	42	47	3.183	1.2466

10.3. The Satisfaction of TF activities

Table 46 shows the results for the satisfaction of TF activities. Participants were asked to evaluate the degree to which they are satisfied with the results of TF at their practices. The 7-point Likert scaled ranged from 'very unsatisfied' to 'very satisfied'. The result indicated that the respondents somewhat satisfied with the results of TF in their organizations.

Table 46 TF satisfaction

Question	Very unsatisfied	Very satisfied	Mean	Std. Deviation
Satisfaction with the results of TF	1	7	4.051	1.519



10.4. The Usefulness of TF on Technology Planning

Table 47 list the results of how TF activities affect the effectiveness of technology planning and strategy in their practices. Based on their previous experience and knowledge, participants were asked to quantify the extent to how they evaluate the usefulness of TF on technology planning activity. The 7-point Likert scaled ranged from 'very negative' to 'very positive'. The result indicated that the respondents think TF activities are useful in establishing technology planning in an effective way.

Table 47 The usefulness of TF in technology planning activity

Question	Very negative	Very positive	Mean	Std. Deviation	
How TF is useful in technology planning activity	1	7	4.71	1.432	

10.5. The Organizational Structure of Effective TF

To identify the organizational structure of effective and efficient TF activity in firms, respondents were asked to rate each organization's effectiveness for efficient TF activity in their firms. As presented in Table 48, 66% of the participants suggested that TF activity within R&D division was the most effective organizational structure of TF. 58% of the participants indicated that TF activity within engineering was the second effective organizational structure of efficient TF. 44% of the participants responded that TF activity comprised of cross functional team were the third effective organizational structure of efficient TF. As a result, this study suggests that TF organization would be better to be placed within R&D division, engineering or cross functional team.



Table 48 Each organization's effectiveness for TF

Organization	Strongly ineffective	Ineffective	Somewhat effective	Effective	Strongly effective	Mean
Within R&D division	5	11	52	85	44	3.772
Within engineering	0	17	65	85	27	3.629
Cross functional team	6	26	76	65	18	3.330
Within business management	3	28	92	65	12	3.275
Within marketing	7	38	88	53	13	3.136
Within operation management	10	55	74	51	7	2.949
Separate TF unit	33	41	42	35	7	2.633
Outsourcing to a consulting firm	34	53	60	34	2	2.546
Outsourcing to academia	39	56	56	24	0	2.371
Outsourcing to national labs	38	60	54	17	0	2.296

10.6. Technology Forecasting and Technology Characteristics

This research examined the relationship between technology forecasting methods and technology characteristics such as basic research, applied research, and development. Q5, 6, 7, 8, and 13 were used in this analysis. The association between seven variables was developed for statistical analysis.

H1a: Qualitative data and technique would be preferable in radical technology innovation.

H1b: Quantitative data and technique would be preferable in continuous technology innovation.



This research investigated the interplay between TF methods, data usage for TF and technology characteristics such as disruptive/discontinuous and continuous technology in TF activities. H1 predicts that the relationship between TF and technology characteristics would be unique. It is based on the assumption that the use of TF methods and data would differ to the nature of technology in a firm as previous studies [26][52][427] pointed out that a firm should pay attention to choose appropriate TF methods and data for forecasting technological changes for a given situation. This study measured TF usages with three different R&D phases.

Pearson correlation test was conducted to examine the association between TF methods, data usage, and R&D stages concerning H1. As shown in Table 49, this research could not find sufficient evidence to reject that the choice of TF tools do not depends on technology characteristics. There was only weak support, indicating the weak relationship between the use of quantitative data and development focus. This is contrary to the proposition this research made in H1 based on previous research [427][428] in the literature. In consequence, these results reveal that many firms in the sample hardly employ appropriate TF methods and data, although they are actively involved in TF activities predicting three to five years forward.

Table 49 The correlation between TF methods, data type, and tech. characteristics

Technology characteristics	The use of qualitative data	The use of quantitative data	TF methods for discontinuous tech	TF methods for continuous tech	
Basic research	0.115	-0.023	-0.027	-0.075	
Applied research	0.041	-0.083	-0.103	-0.092	
Development	0.079	0.141*	0.041	0.061	

Note: *p<0.10, **p<0.05, ***p<0.01. n = 187



Furthermore, this research investigated the use of TF methods based on three different R&D phases. Pearson correlation test was performed to examine the relationship between them. As shown in Table 50, only four TF tools among 20 methods were statistically significant, indicating the association between the use of each technique and technology characteristics. The results indicated that several methods—technology roadmapping and trend extrapolation—have been widely used by firms that involved in the development stage related to continuous/incremental technology, while multi-criteria method has a negative association with the applied research phase. The negative relationship between both data mining and multi-criteria techniques and early phase of R&D reveals that many firms have little knowledge in properly applying these techniques to their applications.

Table 50 The correlation between TF methods and technology characteristics

Technology	Multi-Criteria	Technology	Data Mining; Text	Trend
characteristics	Methods	Roadmapping	(Data) Mining	Extrapolation
Basic research	-0.155	-0.215***	0.138*	-0.040
Applied research	-0.160**	0.041	-0.056	-0.058
Development	0.078	0.268***	0.064	0.141**
N	172	177	186	184

Note: *p<0.10, **p<0.05, ***p<0.01.

10.7. The Use of Hybrid TF Methods and Technology Planning

As prior research suggested that hybrid methods may improve the effectiveness of forecasting by offsetting weaknesses of single forecasting technique, resulting in effective technology planning activity, this study investigated the association between the use of hybrid TF techniques and technology planning activity. Q1, 9, 10, and 11 were used in this analysis. The relationship between four variables was developed for statistical test and SEM.



H2: Combining multiple methods simultaneously has a positive relationship with the effectiveness of TF.

To investigate empirical evidence of whether the use of multiple techniques is associated with the effectiveness of TF in a firm, this study examined the relationship between the use of hybrid methods and the effectiveness of TF. As presented in Table 51, it provides general support for Hypothesis 2 (standardized β = .322, p <.01). Consistent with arguments of prior research [546][24][25], empirical results indicated that the simultaneous use of multiple methods has a positive impact on the effectiveness of TF associated with technology planning. In consequence, this study confirms that combining different TF methods is significant means to enhance the effectiveness of TF associated with technology planning.

Table 51 The correlation between hybrid use of TF methods, TF, and TP

TF characteristics	1	2	3
1. Mutiple use of TF methods	-		
2. Satisfaction with the results of TF	0.322***	-	
3. The usefulness of TF on technology planning	0.269***	0.746***	-

Note: *p<0.10, **p<0.05, ***p<0.01. n = 192

	TF methods	Never heard of it	Hea	rd of it	Read about it	Considered it	Plan to use it	Used it	Currently in use	N
	Trend Extrapolation	16%		21%	10%	10%	3%	23%	17%	174
	Growth Curves; S-Curves	25%		21%	14%	11%	2%	17%	10%	167
	Bibliometrics; Scientometrics	62%		18%	5%	5%	5%	4%	2%	170
	Data Mining; Text (Data) Mining; Tech Mining	3%		16%	17%	14%	6%	22%	22%	175
Explorative TF	System Dynamics	44%		20%	8%	9%	4%	8%	7%	130
	Agent-based modeling	54%		18%	9%	7%	3%	6%	2%	164
	Cross impact analysis	43%		18%	12%	7%	4%	11%	6%	166
	Analogies	28%		21%	15%	10%	2%	15%	8%	168
	TFDEA	65%		11%	10%	4%	3%	4%	2%	167
	Delphi	50%		18%	11%	4%	3%	9%	5%	160
	Nominal Group Technique	31%		10%	6%	8%	4%	22%	19%	159
Normative / Explorative TF	Scenario Planning	20%		11%	6%	8%	9%	22%	24%	162
	Trend impact analysis	21%		15%	6%	12%	5%	23%	19%	160
	Technology roadmapping	10%		7%	4%	8%	4%	20%	47%	162
	Relevance Trees; Decision Trees	46%		20%	8%	9%	3%	9%	6%	158
Narmativa	AHP/ANP	60%		17%	8%	4%	3%	5%	4%	156
Normative	Morphological Analysis	61%		18%	6%	4%	1%	6%	4%	154
	Backcasting	50%		20%	11%	7%	2%	5%	5%	159

Figure 20 The use of TF techniques in practice



Moreover, as illustrated in Figure 20, this study provides a current snapshot of how companies across sectors use TF methods to facilitate strategic technology planning in the U.S-based manufacturing firms. Most companies are familiar with both exploratory/normative and exploratory techniques rather than normative methods. For exploratory/normative tools, many firms employ technology roadmapping (67%), scenario planning (46%), trend impact analysis (42%), and nominal group technique (41%) for predicting technological change. For exploratory methods, most firms among respondents have used data mining (44%), trend extrapolation (40%), and growth curves (27%) in practices. For normative methods, decision trees (15%) are highly used for TF.

10.8. The Industrial Characteristics of TF

This research analyzed research trends of TF tools in the literature and identifies the industry applications among them. The results reveal the industrial aspects of TF tools. TF is critical to every industry. However, in mature industries, technology development tends to be applied to existing product extensions and to process refinements as competitors try to reduce their production costs [316]. Thus, TF activities in emerging or high-tech industry would be higher than in mature industry.



TF Methods	IT	Energy	Aircraft	Machinery	Vehicle	Electronics	Bio/Medical/Health	Transportation	Materials	Services	Food	Environment	Total publications
Trend Extrapolation	3	4			1	3					1		12
Growth Curves; S-Curves	12	12	1		5	14			3		2		49
Bibliometrics; Scientometrics	2	13			2	10	2		2		2		33
Data Mining; Text Mining	11	19			3	11	3	2	2	5	2	5	63
System Dynamics	3	5			3	1	3	1				1	17
Agent-based modeling	1	12			2		2	1		2	1		21
Cross impact analysis	1	1										1	3
Analogies	1					2					1		4
TFDEA	4	1	2		2	5							14
Delphi	11	6		1	4	5	5	5	2		4		43
Nominal Group Technique							1						1
Scenario Planning	7	15				4	3		1		3	2	35
Trend impact analysis							1						1
Technology roadmap	5	16		3	1	19	1				1	3	49
Relevance Trees; Decision Trees	2	1				1	1						5
AHP	2	2	1				1	2	1				9
Morphological Analysis		1				1					1		3
Backcasting	1	7			1			3	1			2	15
Total publications	66	115	4	4	24	76	23	14	12	7	18	14	377

Figure 21 The research share in industry applications in the literature

As presented in Figure 21, among 377 publications, high-tech industries have published a wealth of TF research such as IT, Bio, energy, and electronics, when compared to mature industries such as machinery, aircraft, and food. In light of industry perspective, growth curves, data mining, Delphi, and scenario planning have been widely used in IT industry. Data mining, technology roadmapping, and scenario planning have been mostly employed in the energy sector. Technology roadmapping, growth curves, and data mining have been widely used in electronics sector in the literature. Pavitt and Rothwell pointed out that the nature of the firm's industry may be a more important factor of the character of its innovation [547]. The results might reflect the characteristics or the nature of the industry across sectors. Therefore, this research claims that:

H3: The use of TF techniques differs across sectors.

To investigate the industrial aspects of TF tools with respect to H3, ANOVA was conducted to examine whether there is a significant difference in using TF tools



across industries. As presented in Table 52, the results indicated that there was a weak support for H3. In particular, the use of TF tools hardly differs across sectors. However, the TF activities predicting three to five years or over five years in companies show a statistically significant difference between sectors. The results reveal that electronics, transportation equipment, and chemicals are more likely to actively engage in TF activities within their firms. This outcome has a similarity with the results from bibliometrics.

Table 52 The TF difference across industries

The Use of	df	Mean Square	F	p	
The Has of Evalenatory	Between Groups	15	1.72		
The Use of Exploratory TF Methods	Within Groups	235	2.38	0.722	0.761
1 r Wellous	Total	250			
The Use of Normative	Between Groups	15	1.26		
TF Methods	Within Groups	235	2.73	0.463	0.948
1 r Wellous	Total	250			
The Heave CE-sule sections	Between Groups	15	2.33		
The Use of Exploratory /Normative TF Methods	Within Groups	235	4.85	0.482	0.934
/Normative 17 Methods	Total	250			
TF Activities	Between Groups	15	2.27		
	Within Groups	235	1.11	2.052	0.013**
(3 to 5 years)	Total	250			
TE A stimition	Between Groups	15	2.42		
TF Activities	Within Groups	235	1.29	1.866	0.028**
(over 5 years)	Total	250			

Note: *p<0.10, **p<0.05, ***p<0.01.

10.9. TF Activities based on Technology Characteristics

This research explores the interplay between technology characteristics such as disruptive/discontinuous and continuous technology, TF, and technology planning activities in the design of a performance measurement for R&D activities. Hypothesis 4 predicts that the association between TF activities and technology characteristics would be unique. Q1, 7, 8, and 13 were used in this analysis.



H4: TF activities differ across the type of innovation the firm creates.

It is based on the insight that TF activities in a firm would differ according to the type of innovations a company focuses. This study measures TF and technology planning activities with different stages of R&D process. Pearson correlation test was conducted to identify the relationship between TF activities, action planning (AP), and technology planning (TP) with respect to Hypothesis 4. As presented in Table 53, the results indicated the positive relationship between development stage, AP for one to three years, and TF activity predicting three to five years ahead. However, other stages of R&D have no effect on TF and TP activities within a firm. The results uncover that many firms in the sample are involved in incremental/continuous technology development for commercialization with short-term sights and goals rather than focusing on long-term disruptive/discontinuous product or service development.

Table 53 The correlation between TF activities and technology characteristics

R&D characteristics	Total use of TF	AP(1-3yrs)	TF(3-5yrs)	TF(over 5yrs)	TP
Basic research	-0.08	-0.12	0.03	-0.03	0.001
Applied research	-0.14	0.03	-0.04	0.04	0.12
Development	0.12	0.25***	0.21**	0.07	0.09

Note: *p<0.10, **p<0.05, ***p<0.01.

10.10. TF and Technology Planning

A variety of use of TF makes it difficult to measure its contribution as a source of R&D and business performance. R&D funding is allocated through TF, technology evaluation for project selection, technology strategy, to strategic planning. TF is needed not only to predict promising alternatives but also to assess alternatives in planning process [439]. Therefore, this research claims that:



H5: The use of TF has a positive relationship with technology planning activities in a firm.

Hypothesis 5 theorized that TF activities would have positive relationship with technology planning within a firm. This study found a significant evidence supporting H5 (standardized $\beta = 0.781$, p < .01). Hence, the firms that involve in TF activities are more likely to have active technology planning activities. This is consistent with the results that TF activity plays a critical role in strategic planning and new product development.

Appropriate Use of TF and Technology Planning

The selection of methods mainly affects the accuracy and reliability of TF. If the assumptions are inaccurate, the prediction would go a wrong direction. If TF methods and data are matched and utilized appropriately to the nature of technology in a firm, the effectiveness of technology planning may become distinctive relative to those that are not. For example, one of the mistakes in trend projection most often arise out of the assumption that the future will simply be an addition or subtraction from the present, based on the assumption that technology will follow past trends. It ignores the effects of unprecedented future events. Therefore, most problems in forecasting are caused not by a lack of sophistication but by drawbacks inherent in the process of TF [53]. Therefore, this research claims that:

H6: The appropriate use of data and TF methods improves the firm's capability for technology planning activities.



However, the results did not support Hypothesis 6 that the appropriate use of data and TF methods would have a positive association with the efficacy of technology planning activity for enhancing a firm's competitiveness (standardized $\beta = 0.029$, p > .05). The result reflected that the firms do not use appropriate methods and data based on its characteristics of R&D activities since TF activities has a positive relationship with the appropriate use of TF variable (standardized $\beta = 0.23$, p < .01).

10.11. Firm Size and TF Intensity

This study examined differences in size-related innovative activities by suggesting that the size of a firm would have a positive relationship with TF activities in planning processes within an organization. Large firms are inclined to have more technology planning activities for identifying emerging technologies and market opportunities. Large firms by virtue of their size may have advanced complementary assets. SMEs are more likely to compete for acceptance of their technology rather than capturing new opportunities in their market [548]. Therefore, this research claims that:

H7: The size of a firm has a positive relationship with TF activities in planning processes within organization

Linear regression was performed to identify the relationship between TF activities and firm size after controlling for R&D output with respect to H7. As presented in Table 54, there was strong support, indicating the positive relationship between long-term TF activities and firm size. However, other TF activities including



the use of TF tools have excluded due to multicollinearity issue. Consequently, larger firms have a propensity to involve in long-term TF activities.

Table 54 The linear relationship between firm size and TF activities

Independent variables	Firm size (Total number of employees)		
Main effects	standardized β	p	
TF activities (over 5 years)	0.145	0.014**	
Controls			
Number of patents	0.452	0.000***	
Adjusted R^2	0.249		

Note: *p<0.10, **p<0.05, ***p<0.01.

10.12. Firm Size and the Use of TF Resource

Strategy formulation focuses on organizational resources. In the era of open innovation, many innovative large firms tend to use a wide range of external sources and actors to maintain sustainable capabilities [549]. Thus, the use of external resources plays a vital role to help firms exploit innovative opportunities and gain more knowledge for the sake of their needs. To investigates the organizational functions in TF activities, ANOVA was performed to determine if the use of external or internal TF resources differs based on firm size with F-test regarding H8.

H8: The use of internal/external TF sources differs across the firm size.

As presented in Table 55, this study only found sufficient evidence to reject the null hypothesis for the use of external resources in TF activities. Moreover, supporting H8, comparing the resource-related characteristics of large firms and SMEs reveals that there is a statistically significant relationship between firm size and the use of external resources in TF activities, whereas there is no difference between SMEs and large firms in using internal TF resources and data for predicting technological changes. Due to



lack of internal resource, small firms might be more likely to gain benefits from mainly external TF resources. As a result, however, large firms have a tendency to utilize external resources in TF activities, while small firms are likely to employ internal resources.

Table 55 The linear relationship between firm size and TF resources

Independent Variables	Firm Size (Total # of employees)	External TF resources		Internal TF resources			
Main effects	standardized eta						
External TF	0.164***						
resources Internal TF resources	0.041						
External data	-0.085						
Internal data	-0.004						
Controls							
Total patents	0.744***						
Adjusted R^2	0.547	Mean	S.D.	F	Mean	S.D.	F
Firm size				5.65**			0.066
1. SMEs		2.02	1.11		3.23	0.96	
2. Large firms		2.41	1.17		3.19	1.01	

Note: *p<0.10, **p<0.05, ***p<0.01. For SMEs, n = 94; for large firms, n=105; for total, n=199

10.13. Technology Planning and R&D Performance

High internal planning capability enables a firm to select effectively R&D projects that present themselves fulfilling technological changes. Objective probability of success ratings from TF on selected R&D projects in technology planning process is correlated with the eventual success and failure of these projects. Therefore, this research claims that:

H9: R&D performance has a positive relationship with technology planning activities in a firm.



With regard to H9, this research examined the relationship between technology planning and R&D performance using SEM. As a result, the technology planning would have a positive relationship with R&D performance based on patent activity. The results support H9 (standardized $\beta = 0.241$, p < .01). Technology planning capability has a positive relationship with the level of R&D outputs. Thus, firms with richer TF and TP activities tend to produce better R&D performance.

10.14. Technology Planning and Business Performance

With deliberate attention to strategic technology planning, technology must be managed strategically. TF plays various roles in formulating a business strategy [9] and setting long-term goals. Technological opportunity captured by TF must have a market reference. The question on the relationship between corporate planning and business performance remains unresolved. This study investigated the direct association between technology planning and firm performance.

H10: Business performance has a positive relationship with technology planning activities in a firm.

In terms of H10, this research examined the relationship between technology planning and business performance using SEM. As a result, this research found significant evidence supporting H10 (standardized $\beta = 0.271$ and p < .01) and indicating that technology planning has a positive association with the business performance of a firm. Hence, technology planning capability has a positive relationship with the level of profitability.



10.15. R&D Performance and Business Performance

The association between R&D and business performance has been extensively discussed in various aspects so far in the innovation literature. R&D investment is one of diverse factors that can affect the sales growth and profitability in a firm. A series of empirical studies in the literature have provided mixed support for the relationship between innovation activity and financial performance. Thus, this study revisited this association and SEM is designed to test indirect effect of R&D performance on firm performance.

H11: R&D performance has a positive relationship with business performance of a firm.

To investigate whether R&D performance mediates the relation between technology planning and business performance, a path model was tested using AMOS 22. With respect to H11, this research examined the relationship between R&D performance and business performance. Results indicated that, although technology planning significantly predicted positive effect (standardized $\beta = 0.271$ and p < .01), R&D performance was not significantly related to business performance (standardized $\beta = 0.031$, p > .05). As a result, these findings do not support the hypothesized mediation model. This result is consistent with arguments that patents, as intermediate outputs, are not a direct measure of their commercialization potential [315], that the percentage of innovations patented is limited to maintain secrecy among other reasons [313].



The analyses showed that there was enough evidence to support Hypothesis 2, 4, 5, 7, 9, and 10; weak evidence to support Hypothesis 1 and 8 and no evidence to support Hypothesis 3, 6, and 11. Table 56 presents a summary of the hypothesis testing results.

Table 56 Summary of hypothesis testing

Hypothesis	Result	
The choice of TF methods might depend on	Weak Support	
	11	
	Supported	
-	Supported	
The use of TF techniques will differ across sectors	Not Supported	
TF activities will be different in accordance with the	Supported	
types of innovation the firm offers	Supported	
The use of TF will have a positive relationship with	Supported	
firm's technology planning	Supported	
The appropriate use of data and TF methods will		
enhance the firm's capability for technology	Not Supported	
planning		
The firm size will be positively related with TF	Commonte d	
activities in planning processes within organization	Supported	
The use of internal/external TF sources will depends	Weak Support	
on the firm size		
R&D performance will be a positive function of	Supported	
technology planning activities		
Business performance will be a positive function of	Supported	
technology planning activities		
R&D performance is a positive function of business	Not Supported	
performance of a firm		
	The choice of TF methods might depend on technology characteristics The use of combining multiple methods simultaneously will improve the effectiveness of TF The use of TF techniques will differ across sectors TF activities will be different in accordance with the types of innovation the firm offers The use of TF will have a positive relationship with firm's technology planning The appropriate use of data and TF methods will enhance the firm's capability for technology planning The firm size will be positively related with TF activities in planning processes within organization The use of internal/external TF sources will depends on the firm size R&D performance will be a positive function of technology planning activities Business performance will be a positive function of technology planning activities R&D performance is a positive function of business	



Chapter 11 Discussion

Currently, there is a lack of discussion regarding the impact of a firm's TF activities and technology planning on its performance. This research contributes to the body of knowledge in strategic management and technology management in a couple of ways. First, this study tackles the issue of how the outputs and outcomes of R&D activities can be measured. The main issue with measuring R&D outputs and outcomes stems from the fact that they are a multi-dimensional phenomenon. This research explores the metrics of R&D and business performance and proposes linkages between TF, technology planning, R&D performance, and business performance based on the literature review. Furthermore, this study verifies the hypotheses using the structural equation model. The results showed that there was enough evidence to indicate the positive associations between TF, technology planning, R&D performance, and business performance, supporting Hypotheses 5, 9 and 10. However, this study found weak evidence to support Hypothesis 6 and no evidence to support the positive association between R&D performance and business performance (H11), which is still controversial in the literature. Taken together, the results reveal the interactive effect of TF and technology planning activities on a firm's business performance.

The results extend previous research on firm performance by elaborating on the association between technology characteristics, various technology management activities, R&D outputs, and firm performance. Consistent with expectations, empirical results indicate that planning capability has a positive relationship with the level of profitability. As measured by sales growth, ROA, and earnings growth, firms with higher TF and R&D planning activities are more likely to have better financial



performance. Moreover, as measured with patents granted, firms with richer TF and TP activities have a tendency to produce better R&D performance. Consistent with a resource-based view, the results indicate that companies are able to acquire and sustain a competitive advantage through effective TF and technology planning activities. Patents as an innovation output showed an insignificant relationship with firm performance. This result is consistent with arguments that patents, as intermediate outputs, are not a direct measure of their commercialization potential [315], that the percentage of innovations patented is limited to maintain secrecy among other reasons [313]. Thus, patents would be regarded as a measure of inventive output rather than innovative success. In other words, it would be possible that overinvested R&D activities may erode a firm's profitability.

In addition, there is currently a lack of discussion in understanding firms' TF activities and technology planning in technology and innovation management literature. This study analyzed trends in TF research both in methods and applications. This research presents how TF research has evolved in the literature on technology and innovation management with the overview of chronological evolution, identifies the current trends, and discusses various characteristics in a variety of TF methods. Based on the literature review, this study explores the use of TF in various ways—TIMO aspects—for providing managerial implications of TF to an organization's application. The results are based on an examination of multiple dimensions of TF, and provide empirical findings not only to identify research trends but to select applicable and practical TF methods for future study in different fields. This research provides basic guidance and evidence with respect to TF activities in practice by statistically



examining five propositions. This study contributes to the body of knowledge in strategic technology management in various ways.

First, technological implications of this study reveal that many firms hardly use appropriate TF methods and data, although they have conducted three to five years of TF activities. Consistent with prior research [26][52], the results confirm that determining appropriate TF methods is critical for a given situation in order to predict technological changes in accordance with the technology characteristics. R&D managers should hone their technology planning skills associated with TF even more than they already have. The results suggest that management group should deepen their knowledge of TF techniques and data usage based on their R&D focus for taking benefits out of it. Moreover, firms should identify and develop their own distinct and effective approaches for capturing emerging opportunities/threats. For example, if firms focus on applied or basic research, they should adopt normative approaches and qualitative data. In this regard, this study helps to identify whether a firm uses appropriate TF tools to predict technological changes for its strategic management of technology planning or not. In consequence, experience and expertise in various TF techniques and data usage is an important element in expanding a firm's innovative capability.

Second, this research provides statistical evidence to support that the use of composite TF techniques is a significant means to enhance the effectiveness of TF. The methodological implications: firms should have more knowledge in combing TF techniques to identify opportunities/threats effectively. Thus, preferred approaches would incorporate hybrid TF tools, not simply relying on any single TF method. This



study provides several conclusions as to how to integrate two or more approaches into the decision-making process. Moreover, this study identifies research trends and the practices of TF methods in industry. Both researchers and practitioners have mainly used data mining, growth curves, scenario planning, and technology roadmapping for predicting technological changes. While bibliometric, Delphi, and AHP/ANP are typically used for TF in the literature; trend impact analysis, nominal group technique, and decision trees are widely utilized in practice. The discrepancy between research and practice might partially stem from the fact that the expert-based tools are not easily implementable for TF analysis in practice; many techniques applied by corporations are introduced by consulting firms that help companies adopt them and increase their use of TF methods in responding to drastic competition among them. As a result, researchers should put more effort into introducing novel methods or enhanced applications for providing the better implementable measures based on various types of data in practice.

Third, the TF activities in corporations show dissimilarity between industries. However, the results of the industrial aspects of TF suggested weak support of that the use of TF tools differs across sectors, similar to the results from bibliometrics. There might be no support of the myth that there are "high technology industries" and "low technology industries." The results reflect that many firms in each sector seldom use appropriate TF methods in accordance with industry characteristics. This study also identifies that researchers focus on TF studies related to IT, electronics, and energy in the literature. Moreover, the use of TF tools in practice reinforces this finding of bibliometrics. Firms in electronics and chemicals tend to utilize a variety of TF methods.



Fourth, systematic TF in strategic planning processes can reduce firms' vulnerability to changes of industry structure and industry evolution. Technology management groups should focus their attention on which stages of evolution in which they engage, and intensify their expertise in technological and structural characteristics in which they are involved. For instance, firms that engage in the late mature stage should become skilled at predicting whether such markets can be substituted by other technologies/products, and deciding the types of technological capabilities that will be needed to sustain the substitution effort. However, firms that are in development or in the growth stages of evolution would be good at predicting technology using exploratory TF methods and data. Thus, they need to become strategic technology planning experts in the industries in which they invest. In addition, they should continue to seek opportunities/threats that enable them to develop a unique product or service features in order to achieve sustainable competitiveness.

Finally, if an SME lacks resources, it should use the informal network to get informed of technological changes [550]. Although many studies pointed out that SMEs are required to take advantage of external resources, firms in the sample of this study represented that they depend on internal resources led by entrepreneurs who have technical skills for predicting technological changes in strategic technology planning. The results indicated that the role of the entrepreneur is crucial in developing technology, which is consistent with the previous studies [551]. Consequently, the key determinant of R&D success in SMEs would be the capability of a technical entrepreneur to develop strategic technology planning. Technical entrepreneurs would be a critical source of their competitive advantage. Regardless of firm size, this research



suggests that a firm should proactively seek out internal or external persons who have detailed knowledge of strategic technology planning and TF principles.



Chapter 12 Conclusions and Contributions

Although strategic management research has expanded and increased since the 1960s, the technology planning-performance relationship has been poorly understood. The assumption that technology planning provides economic value was adopted since it was consistent with findings in prior planning-performance research. This research provides arguments based on both RBV and dynamic capability and describes an empirical trial. This study concludes that TF and firm performance are more highly associated with planning disequilibrium industries. The greater degree of technology planning linked with TF reflects a firm's dynamic capability rather than planning disequilibrium. An attempt was made to identify sectors with different levels of TF dissemination. The results weakly supported the difference in TF across industries. The important contribution of this study is, however, its linkage of technology planning with TF and firm performance, as a potential source of competitive advantage. The TF process is a strategic asset with competitive advantage, in the long run, as a fundamental organizing category for the strategic planning field.

This research contributes to the current literature by proposing an appropriate organizational decision making process to implement effectively in TF activities and to aid in strategic planning and technology development. One of the contributions of this study is to elaborate on the perceived usefulness of TF methods for new product and service development and its connection to the organizational or industry characteristics of the firm. This study provides a comprehensive illustration of TF tools in order to assist policy makers, universities, research institutes/national labs and companies to enhance the decision making process on technology development and new research



fields. The strategic decision support process identified in this study fills a gap that a company is facing in a turbulent environment with a view toward emerging technology fields. This model provides various types of values as follows:

- i. A decision maker can effectively identify emerging technologies with the aid of TF activities in a firm.
- ii. Universities, research institutes, and national labs can capture areas of research focus with the use of the effective TF techniques identified in this study.
- iii. Companies can identify the direction of customer needs and areas of commercialization endeavors.

This research not simply identifies research gaps but also selects applicable and practical TF methods for future study. This study identified whether the use of multiple perspectives merging the normative and the exploratory approach could improve the effectiveness of forecasting technological change. In summary, this study provides a comprehensive TF activity for the researchers and practitioners.

Contributions to strategic management

This study attempts to present findings useful for consideration in an integrated innovation framework. Major findings in this research provide important implications for work on TF, strategic technology planning, technology assessment, and firm operation. As presented in Figure 22, this research provides a systematic process as to when, where, and how to implement TF activities in strategic planning in accordance with several critical factors—industry structure, the stage of industry life cycle, the stage of innovation, technology characteristics, available data, and techniques.



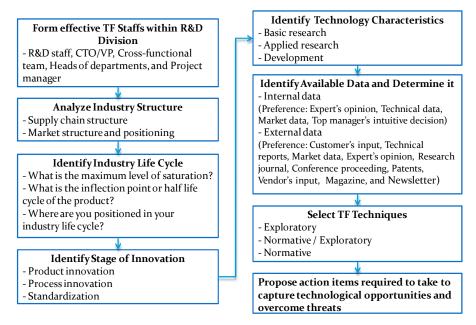


Figure 22 Systematic decision-making process for strategic technology planning

First, the advantage of the proposed research is to provide appropriate organizational decision-making metrics to effectively aid in strategic technology planning and technology assessment. This research attempts to present findings useful for considering an integrated innovation management framework. Major findings in this study provide important implications for work on TF, strategic technology planning, and firm operation. The hypothetical framework presented in this research not only provides a current snapshot of how firms across industries implement best practices in TF to facilitate organizational functions and strategic technology planning in the U.S. manufacturing firms but also improves the effectiveness of TF in strategic planning by capturing technology characteristics in various industries. This study provides a comprehensive illustration of some of the most common metrics used for evaluating R&D performance and business performance in order to assist policy makers,



universities, research institutes/national labs, and companies to enhance the decision making process on technology development and new research fields.

The empirical results reveal that most of the firms put an effort to predict short-term technological changes, focusing on short-term profitability regardless of firm size. However, not all R&D efforts may result in quick financial returns. Short-term sights and goals for product or service development are likely to produce a negative association between R&D activities and firm performance. R&D is not a clear-cut process. Technological innovations typically take a long time to make a predictable or unpredictable commercial success [394]. For example, Dupont took about ten years to introduce nylon products to customers [395]. In this regard, the recommendation out of the results is that a firm should support short-term and long-term TF activities when it focuses on the applied research and basic research as well, enhancing its focal products to flourish.

Contributions to managerial aspects

For managerial implications, TF activities were found in firms to yield more efficacy of technology planning activities which overall results in improved business performance. This has managerial implications: there is strong evidence that a firm should emphasize the importance of TF activities in technology planning to sustain competitiveness in the market. Recently companies have realized how important these efforts are and have attempted to improve current practices. The results were consistent with the findings in prior TF-performance research [378][552]. The results in this study extend the literature by showing that with strategic technology planning, TF activities have a positive association with ROA, earnings growth, and sales growth. Moreover,



this research identified the difference in data usage based on the firm size. This study also found the difference in TF methods based on the type of innovation stage.

Therefore, decision makers need to determine TF methods/data and TP strategies in accordance with technology characteristics, firm size, and their goals (R&D and business performance), as presented in Figure 23.

Goals	Size	Type of innovation	Data	Methods	
R&D	Large	Basic	Customers input, Technical reports, Research journals, Patents, External experts opinions, External market data	Data Mining, Analogies, Cross Impact Analysis	
performance		Applied	Customers input, Technical reports, Research journals, Patents, External experts opinions, External market data	Scenario Planning, Cross Impact Analysis, Analogies	
		Dev.	Customers input, Technical reports, Research journals, Patents, External experts opinions, External market data	Technology Roadmapping, Scenario Planning, Trend Extrapolation, Trend Impact Analysis, Growth Curves	
	SMEs	Basic	Internal Expert's opinion, Internal Technical data, Internal Market data, Top manager's intuitive decision	Data Mining, Analogies, Cross Impact Analysis	
		Applied	Internal Expert's opinion, Internal Technical data, Internal Market data, Top manager's intuitive decision	Scenario Planning, Cross Impact Analysis, Analogies	
		Dev.	Internal Expert's opinion, Internal Technical data, Internal Market data, Top manager's intuitive decision	Technology Roadmapping, Scenario Planning, Trend Extrapolation, Trend Impact Analysis, Growth Curves	
Business	Large	Basic	Customers input, Technical reports, Research journals, Patents, External experts opinions, External market data	Data Mining, Analogies, Cross Impact Analysis	
performance				Customers input, Technical reports, Research journals, Patents, External experts opinions, External market data	Scenario Planning, Cross Impact Analysis, Analogies
		Dev.	Customers input, Technical reports, Research journals, Patents, External experts opinions, External market data	Technology Roadmapping, Scenario Planning, Trend Extrapolation, Trend Impact Analysis, Growth Curves	
	SMEs	Basic	Internal Expert's opinion, Internal Technical data, Internal Market data, Top manager's intuitive decision	Data Mining, Analogies, Cross Impact Analysis	
		Applied Internal Expert's opinion, Internal Technical data, Internal Market data, Top manager's intuitive decision		Scenario Planning, Cross Impact Analysis, Analogies	
		Dev.	Internal Expert's opinion, Internal Technical data, Internal Market data, Top manager's intuitive decision	Technology Roadmapping, Scenario Planning, Trend Extrapolation, Trend Impact Analysis, Growth Curves	

Figure 23 TF data and methods based on technology characteristics and firm size

Clearly, firms can benefit from predicting technological changes that not only affect the market and industry structural changes but also create new supply chains and market segments. The identification of the distinct characteristics of effective technology planning is proven to be a fruitful focus for firms' performance. R&D managers should hone their technology planning skills linked with TF even more than they already have. Integration of equivalent TF and planning capabilities and R&D



efforts enables a firm not only to increase R&D productivity but also to achieve financial success. Hence, the results suggest that an executive management group should enhance their core competence by improving sensing and planning activities.

Second, the results suggest that a management group also should deepen their knowledge of TF techniques and data usage based on their R&D focus. Moreover, firms should identify and focus on their own distinct and effective approaches to generate expected R&D outputs and financial outcomes by capturing emerging trends. For example, while firms are involved in applied or basic research, they should adopt normative approaches and qualitative data. Besides, facing the drastic technological change on its turf, a firm's planning activities should pay attention to appropriate TF tools and data. The previous research [427] helps to identify whether a firm uses appropriate TF tools for predicting technological changes in its strategic management of technology planning. Figure 23 illustrates the systematic process as to how to select appropriate TF tools for specific cases.

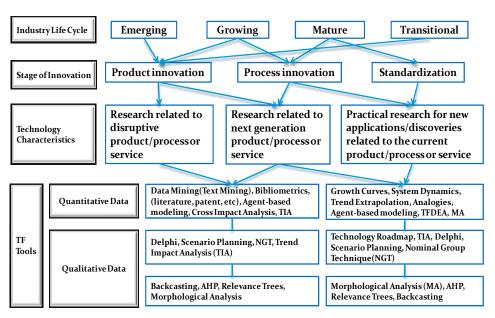


Figure 24 Guidance of appropriate selection with respect to TF activities



If firms understate TF activities based on technology characteristics, ineffective planning might deteriorate the subsequent R&D outputs and thus result in poor business performance. Consequently, experience and expertise in various TF techniques and data usage is an important complementary asset in expanding a firm's innovative capability. Firms should screen their ideas along with TF to help ensure that they can make an effective strategic decision in the fuzzy front end of new product development.

Finally, in accordance with best practices in TF, firms can gain insight into industry dynamics as well as how to deal with the changing environments that they face. Strategic technology planning associated with TF seems to have value for companies that focus on R&D activities. The results advance the role of TF in strategic planning as a capability. As a firm has a deeper understanding of TF in strategic technology planning, there is the potential for turning the systematic process toward dynamic capability. As Teece [553] describes this process—sensing and capturing opportunities—this research characterizes systematic strategic technology planning processes as a resource and potential source of competitive advantage. According to a dynamic perspective, the proposed systematic technology planning process should be adapted and evolved for specific conditions and integrated into other organizational processes.



Chapter 13 Limitations and Future Research

Survival in every sector now depends on technological innovations leading to innovative products and services and their successful commercialization. Meanwhile, the literature concerning TF activity for particular situations—technology characteristics, market structure, and industry evolution—is still scarce. This study provides basic decision-making guidelines for firms, government agencies, and researchers to effectively implement in TF activities for supporting strategic technology planning as well as implementing R&D projects in their field. The results of this research help decision makers or forecasters select appropriate techniques in their business domains. Thus, it is significant to note that it requires experience and expertise in various TF techniques to select appropriate TF methods.

One of the limitations is that this study did not measure objective financial performance—sales growth, ROA, and earnings growth, respectively, but instead inferred them from survey respondents' subjective measures. Further research is required to illuminate the association between R&D capabilities and actual firm performance. Future research should further investigate the strategic decision making process of technology planning to identify additional criteria to measure R&D performance related to financial performance. Special care should be taken to identify any other contingent parameters employed in strategic decision-making in the manufacturing sector. Efforts to identify such key factors of R&D outputs and capabilities might substantially strengthen both firms' practices and academic research.

The other limitation is related to the notion of causality. This research considered the use of TF and technology planning activities as it relates to enhancing



both R&D performance and business performance. The results only guarantee the high probability of predicting events rather than the ability to control events. Thus, it allows a limited degree of control. The SEM method cannot prove causation. The relationship between planning and performance still lacks theoretical grounding. A further study may help uncover causation or demonstrate associations between those variables.

Despite these limitations, future research should pay more attention to utilize appropriate TF methods and data in strategic technology planning.

Numerous factors may influence a firm's decision to invest in innovation activities. Hence, future research should examine more carefully the impacts of R&D outputs on financial performance. Several studies indicated that R&D investments are highly associated with a firm's level of innovation performance [554]–[556]. Prior research indicated that R&D expenditure has a positive relationship with firm size [556][557]. Moreover, it would be important to analyze multiple perspectives on complex system issues such as societal and institutional environment aspects in this model. Thus, other issues associated with R&D investment and firm performance should be discussed by further empirical research design. Therefore, it would seem reasonable that future research should focus on comprehensive linkages as illustrated in Figure 5.

Further research is needed to verify the efficiency and effectiveness of combining methods for comparing outcomes in this research. This research was mainly conducted in the U.S. and it could be extended to other regions for comparison of the results. To apply this framework further in a different setting, the survey could be distributed to a more geographically dispersed sample set in the world for comparison.



For example, interesting follow-up studies might investigate other countries in order to examine cultural or environmental differences. Abstract-based or keyword-based coword analysis in the literature with respect to composite TF techniques may be ripe for a quantitative analysis of the relationship among TF methods. It might be useful to identify TF tools based on the product and service category. Further improvements including managerial implications based on firm size are recommended. Lastly, more comprehensive reviews including econometrics, correlation method, and a causal model would benefit the analysis.

In spite of several limitations, it is meaningful that this research provides a current snapshot of how firms across industries implement best practices in TF to facilitate organizational functions and strategic technology planning in the United States. The study also presents an informative research focus as well as potential research gaps in TF fields to the researchers and practitioners. New approaches with the different combination of TF tools would be open to all researchers and practitioners.



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Appendices

Appendix A. Human Subjects Approval



Post Office Box 751 503-725-2227 tel Portland, Oregon 97207-0751 503-725-8170 fax Research Integrity (Research & Strategic Partnerships) IRB (Human Subjects Research Review Committee) hsrrc@pdx.edu

Date: January 31, 2017

To: Tugrul Daim and Joseph Cho, Engineering & Technology Management

From: Lindsey Wilkinson, IRB Chair

Re: IRB review determination for your protocol #163982, entitled: "Exploring technology forecasting and its

implications for strategic technology planning"

Notice of IRB Review and Determination - Initial Review Exempt Review Category #2; as per Title 45 CFR Part 46

In accordance with your request, the PSU Research Integrity office, on behalf of the IRB (Human Subjects Research Review Committee), has reviewed and approved your protocol for compliance with PSU policies and DHHS regulations covering the protection of human subjects. Research Integrity has determined your protocol qualifies for exempt review and is satisfied that your provisions for protecting the rights and welfare of all subjects participating in the research are adequate. Please note the following requirements:

Approval: You are approved to conduct this research study after receipt of this approval letter, and the research must be conducted according to the plans and protocol submitted (approved copy enclosed).

Consent: You must use IRB-approved consent materials with study participants.

Changes to Protocol: Any changes in the proposed study, whether to procedures, survey instruments, consent forms or cover letters, must be outlined and submitted to Research Integrity immediately. The proposed changes cannot be implemented before they have been reviewed and approved by Research Integrity.

Adverse Reactions and/or Unanticipated Problems: If any adverse reactions or unanticipated problems occur as a result of this study, you are required to notify Research Integrity office within 5 days of the event. If the issue is serious, approval may be withdrawn pending an investigation by the IRB.

Completion of Study: Please notify Research Integrity as soon as your research has been completed. Study records, including protocols and signed consent forms for each participant, must be kept by the investigator in a secure location for three years following completion of the study (or per any requirements specified by the project's funding agency).

If you have questions or concerns, please contact the Research Integrity office in Research & Strategic Partnerships at hstrategic.pdx.edu or call 503-725-2227.



01/6/2017

Portland State University Office of Research Integrity

Informed Consent Form

You are invited to participate in a research study, conducted by Ph.D. candidate Joseph Cho and faculty member Tugrul Daim with the Engineering & Technology Management department at Portland State University, about how companies conduct technology forecasting or technology planning activities and we are contacting you because you are the CEO, CTO, or General Manager in charge of R&D.

The purpose of this research is to provide a more intensive investigation of the organizational, technological, methodological, and industrial context in which technology forecasting or technology planning activities are, or are not, found. In addition, it will provide comprehensive evidence on the extent and nature of technology forecasting in industry. We are living in a drastically changing world. You might use different terms or activities for technology forecasting or technology planning to do the same or similar things in your organization. If you are unfamiliar with technology forecasting, here is a brief explanation: In 1962 Lenz, one of the pioneers of technology forecasting, defined technology forecasting as "the prediction of the invention, characteristics, dimensions, or performance of a machine serving some useful purpose The qualities sought for the methods of prediction are explicitness, quantitative expression, reproducibility of results, and derivation on a logical basis."

There are no known risks if you decide to participate in this research study. There are no costs to you for participating in the study. The information you provide will be used to complete the requirements of a doctoral degree, and may be published in aggregate form. The questionnaire will take about 10 minutes to complete. While the information collected may not benefit you directly, the information learned in this study should provide more general benefits.

This survey is anonymous. We are sending anonymous link not collecting IP addresses. No one will be able to identify you or your answers, and no one will know whether or not you participated in the study. Individuals from the Institutional Review Board may inspect these records.

Your participation in this study is voluntary. By completing the survey, you are voluntarily agreeing to participate. You are free to decline to answer any particular question you do not wish to answer for any reason.

If you have any questions about the study, please contact Joseph Cho at yonghee@pdx.edu or by phone at 503-616-0218, or contact Tugrul Daim (faculty advisor) at tugrul.u.daim@pdx.edu.

The Portland State University Institutional Review Board has reviewed this project. If you have any concerns about your rights in this study, please contact the PSU Office of Research Integrity at (503) 725-2227 or email hsrrc@pdx.edu.

If you feel that someone else is better qualified to fill out the survey, please forward this survey to him or her. If you are interested in the results of this research, we are more than happy to send the summary of this survey results and document as well. As a sign of pappy existing for

_____1/31/2017___ Portland State University Office of Research Integrity

RECEIVED

01/6/2017

Portland State University

your feedback, we will provide ten \$70 Amazon gift cards to randomly selected to randomly sel

Thank you very much for your time and help.



Appendix B. Survey Questionnaire

. To start and proceed the survey, please click next arrow at the bottom of the page

Informed Consent Form

You are invited to participate in a research study, conducted by PhD candidate Joseph Cho and faculty member Tugrul Daim with the Engineering & Technology Management department at Portland State University (PSU), about how firms conduct technology forecasting or technology planning activities and we are contacting you because you are the CEO, CTO, Vice President, or General Manager in charge of Research and Development (R&D).

The purpose of this research is to provide a more intensive investigation of the organizational, technological, methodological, and industrial context in which technology forecasting or technology planning activities are, or are not, found. In addition, it will provide comprehensive evidence on the extent and nature of technology forecasting in industry. You might use different terms or activities for technology forecasting or technology planning to do the same or similar things in your organization. If you are unfamiliar with technology forecasting, here is a brief explanation: In 1962 Lenz, one of the pioneers of technology forecasting, defined technology forecasting as "the prediction of the invention, characteristics, dimensions, or performance of a machine serving some useful purpose The qualities sought for the methods of prediction are explicitness, quantitative expression, reproducibility of results, and derivation on a logical basis."

There are no known risks if you decide to participate in this research study. There are no costs to you for participating in the study. The information you provide will be used to complete the requirements of a doctoral degree, and may be published in aggregate form.

The guestionnaire will take about 10 minutes to complete.

While the information collected may not benefit you directly, the information learned in this study should provide more general benefits. This survey is anonymous. We are sending anonymous link not collecting IP addresses. No one will be able to identify you or your answers, and no one will know whether or not you participated in the study. Individuals from the Institutional Review Board may inspect these records. Your participation in this study is voluntary. By completing the survey, you are voluntarily agreeing to participate. You are free to decline to answer any particular question you do not wish to answer for any reason.

If you have any questions about the study, please contact Joseph Cho at yonghee@pdx.edu or by phone at 503-616-0218, or contact Tugrul Daim (faculty advisor) at tugrul.u.daim@pdx.edu. The Portland State University Institutional Review Board has reviewed this project. If you have any concerns about your rights in this study, please contact the PSU Office of Research Integrity at (503) 725-2227 or email hsrrc@pdx.edu.

If you feel that someone else is better qualified to fill out the survey, please forward this survey to him or her.

If you are interested in the results of this research, we are more than happy to send the executive summary of this survey results and document as well. As a sign of appreciation for your feedback, we will provide seven \$70 Amazon gift cards to randomly selected participants after completion of this survey.

Thank you so much for your time and help.



Basic Info..

Please provide your basic information	n to verify your response.	
Company:		
Total No. of employees of your firm		
Position:		
Industry experience(years):		
City		
State		
Zip Code		

Q1. Which of the following activities are conducted in your organization? (Multiple Choices) (Note: If you place your mouse on each answer, you will notice the definition of each terminology)

	No use	Not often conducted	Somewhat often conducted	Often conducted	Very often conducted
Market Forecasting	0	0	0	0	0
Technology Forecasting (three to five years)	0	0	0		0
Technology Forecasting (over five years)	0	0	0		0
Technology Planning					\circ
Short-term Forecasting (less than one year)	0	0			0
Annual Planning					\bigcirc
Action Planning or Operational Planning (one to three years)	0	0	0	0	0
Strategic Planning (three to five years)	0	0	0	0	0
Long-range Planning (over five years)	0	0	0	0	0
Others (Please, specify it)	0	0	0	0	0



Q2. If your firm conducts technology forecasting for each of the following purposes, how do you rate the importance of technology forecasting performed by your planning staff(s) in your organization. (Multiple Choices)

	Of no use	Not important	Moderate	Important	Extremely important
As an aid in business planning and strategy	0	0	0	0	0
As an aid in R&D or technology planning					0
As an aid in allocating resources	0				0
As an aid in evaluating projects					
To help justify a previously made decision					
To help in acquiring a government contract or subcontract			0		
To assess technology portfolios			0		
To redesign business or manufacturing process					0
To develop a new product or service			0		
To identify new opportunities or hreats	0		0		
Others (Please, specify it)	0		0		

Q3. Who are involved in technology forecasting activities within your organization? (Multiple Choices) Please, rate how effectively they are engaged in technology forecasting activities.

	Strongly ineffective	Ineffective	Somewhat effective	Effective	Strongly effective
Research and Development (R&D) staff	0	0	0	0	0
Project engineering staff					
Operation management staff					
Business management staff					
Marketing staff					
Cross functional team					
Heads of departments					
CTO/VP of Engineering					
CEO	0				
Outside consultants/experts in a private company	0				0
External experts from national labs	0				
External experts from academia	0				
Others (Please, specify it)	0				0



Q4. Based on your knowledge and experience about applicable organizational structure of technology forecasting, please rate each organization's effectiveness for efficient technology forecasting activities? (Multiple Choices)

	Strongly ineffective	Ineffective	Somewhat effective	Effective	Strongly effective
Within R&D Division	0	0		0	
Within Engineering	0	0			
Within Business Management	0	0			
Within Operation Management					
Within Marketing	0				
Cross Functional Team	0				
Outsourcing to a consulting firm	0	0			
Outsourcing to academia	0				
Outsourcing to national labs					
Separate Technology Forecasting Unit	0	0	0	0	0
Others (please specify it)	0		0	0	0

Q5. What sources of data does your organization often use to forecast technological changes while conducting technology planning or other planning activities within your firm? (Multiple Choices)

	No use	Not often	Somewhat often	Often	Very often
Newsletters	0	0	0	0	0
Magazines			0		
Conference proceedings	0		0		\circ
Technical reports					
Research journals					
Patents					
Internal technical data			0		
External experts opinions			0		
Internal experts opinions	0		0		\circ
Intuitive decision of top managers	0	\circ		0	0
Internal market data					
External market data					
Vendors input					
Customers input	0				
Others (please specify it)	0	0		0	0



Q6. In your opinion, what sources of data would help your organization in technology forecasting for planning activities ? (Multiple Choices)

	Of no use	Not important	Moderate	Important	Extremely important
Newsletters	0	0		0	
Magazines					
Conference proceedings					
Technical reports					
Research journals					
Patents		0			
nternal technical data					
External experts opinions					
nternal experts opinions					
ntuitive decision of top managers					
Internal market data					
External market data					
Vendors input					
Customers input					
Others (please specify it)	0				

Q7. How familiar are you with each of the following 'exploratory' technology forecasting methods? (exploratory; forecasting starts from the present using historical data) (Note: If you place your mouse on each answer, you will notice the definition of each terminology)

	Never heard of it	Heard of it	Read about it	Considered it	Plan to use it	Used it	Currently in use
Trend Extrapolation	0						
Growth Curves; S-Curves, BASS Model	0						
Bibliometrics; Scientometrics	0						
Data Mining; Text (Data) Mining	0	0					
Growth Analogies; Comparison-Based Prediction		0					
Cross Impact Analysis							
System Dynamics							
Technology Forecasting Using Data Envelopment Analysis (TFDEA)	0	0	0	0	0	0	0
Multivariate Analysis	0						
Environmental Scanning							
Probabilistic Forecasts							
Life Cycle Analysis			0				
Agent-Based Model							
TRIZ (The theory of inventive problem solving)	0	0	0		0	0	0
Others (please specify it)	0	0	0				



Q8. What is your level of familiarity with each of the following 'normative' technology forecasting methods? (normative; forecasting begins with the future environment or scenario)
(Note: If you place your mouse on each answer, you will notice the definition of each terminology)

		Never heard of it	Heard of it	Read about it	Considered it	Plan to use it	Used it	Currently use
Relevance Trees		0		0	0	0	0	0
Analytic Hierarchy F AHP), Analytic Net Process (ANP), Mu Decision Model	work					0	0	0
Morphological Anal	ysis					\circ	\bigcirc	
Backcasting						\bigcirc	\circ	
<u>Delphi</u>								
Nominal Group Tec NGT); Brain Storm		0	0	0	0	0	0	0
Scenario Planning /	Writing						\bigcirc	
rend Impact Analy	rsis							0
echnology Roadm	apping							
Survey							0	
ocus Group Interv	iew						0	0
Planning Assistance Technical Evaluatio Relevance Number PATTERN)	n of		0			0	0	0
Simulation and Gar	nes					\bigcirc		\bigcirc
Risk Analysis						\bigcirc		
Others (please spec	cify it	0	0	0	0	\circ	0	0
Q9. Has your com		d two or mor	e technology	/ forecasting	tools simultar	neously to imp	prove the e	ffectivenes
3,	No		Do	not know			Yes	
Q10. Based on yo			ge, to what	degree are yo	ou satisfied w	ith the results	of technol	ogy
Very Unsatisfied 1	2	3		4	5	6	Ver	y Satisfied 7
	0	0		0	0	0		0
Q11. Based on yo					nology forec	asting activitie	es affect the	е
Very Negative 1	2	3		4	5	6	Ver	y Positive 7
0		0		0	0	0		0
Q12. What propo	rtion of revenu	es does you	company in	vest in Rese	arch & Devel	opment?		
Do not know	less than 1%	1-3%		3-5%	5-7%	7-10%	. (over 11%
	_			_				



Q13. What proportion of your R&D effort (in terms of human and financial resource) is spent on the product or service developments?

(Please make	sure that it appr	roximately adds	up to 100%)
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	Less than 10%	10-20%	20-30%	30-40%	40-50%	50-60%	60-70%	70-80%	80-90%	90- 100%
Fundamental or basic research (for the sake of knowledge related to disruptive product/process or service)	0	0	0	0	0	0	0	0	0	0
Applied research (directly related to next generation product/process or service)	0	0	0	0	0	0	0	0		0
Development (new applications/discoveries to the current product/process or service)	0	0	0	0	0	0	0	0	0	0

Q14. Please indicate the magnitude of changes of your business over the last five years. (Note: If you place your mouse on each answer, you will notice the definition of each terminology)

,	1	5,7							
	Less than -30%	-10 to -20%	>= -10%	0	<= 10%	10 to 20%	Over 30%		
Sales growth	0	0	0		0	0	0		
Return on assets (ROA)	0		\bigcirc			\circ			
Earnings growth	0								
<u>Market share on your most</u> relevant market	0		0	\circ		0	\circ		
Your competitive position in general	0		0	0		0	0		

. Are you interested in receiving t	the summary	results of this	research?
-------------------------------------	-------------	-----------------	-----------

Yes	No
0	0

Contact Info.

Please make sure to provide your email address and contact information to receive the results of this research, but also to be eligible to win a gift card:

First name:	
Last name:	
Last Harrie.	
Email:	
Fax:	



Appendix C. Variables (Descriptive Statistics)

Variables	Min.	Max.	Mean	Std. Deviation
Technology forecasting				
(3 to 5 years)	1.0	5.0	3.498	1.0872
Technology forecasting	1.0	5.0	2 976	1 1660
(over 5 years)	1.0	5.0	2.876	1.1660
Technology planning	1.0	5.0	3.723	.9936
Short-term forecasting	1.0	5.0	4.183	1.0703
(less than 1 year)	1.0	5.0	4.103	1.0703
Annual planning	1.0	5.0	4.398	.9121
Action planning or operational	1.0	5.0	4.082	.9678
Planning (1 to 3 years)	1.0	5.0	4.062	.9078
Strategic planning	1.0	5.0	3.864	1.0636
(3 to 5 years)	1.0	5.0	3.004	1.0030
Long-range planning	1.0	5.0	3.183	1.2466
(over 5 years)	1.0	5.0	5.105	1.2400
As an aid in business planning and	1.0	5.0	3.890	.9391
strategy	1.0	5.0	3.070	.,,,,,,
As an aid in R&D or technology	1.0	5.0	4.060	.9406
planning				
As an aid in allocating resources	1.0	5.0	3.648	.8724
As an aid in evaluating projects	1.0	5.0	3.664	.8290
To help justify a previously made	1.0	5.0	2.868	.9935
decision	1.0	2.0	2.000	.,,,,,
To help in acquiring a government	1.0	5.0	2.284	1.1635
contract or subcontract				
To assess technology portfolios	1.0	5.0	3.143	1.1558
To redesign business or	1.0	5.0	3.306	1.0148
manufacturing process	1.0	2.0	2.500	1.0110
To develop a new product or	1.0	5.0	4.087	.8866
service	- 1.4			
To identify new opportunities or	1.0	5.0	4.037	.9426
threats	-			
Research and Development (R&D)	1.0	5.0	3.895	.9726
staff				
Project engineering staff	1.0	5.0	3.471	.9405
Operation management staff	1.0	5.0	3.148	1.0223
Business management staff	1.0	5.0	3.455	1.0381
Marketing staff	1.0	5.0	3.300	1.0629
Cross functional team	1.0	5.0	3.505	.9700
Heads of departments	1.0	5.0	3.474	.9610
CTO/VP of Engineering	1.0	5.0	3.882	.9930
CEO	1.0	5.0	3.380	1.1426
Outside consultants/experts in a	1.0	5.0	2.759	1.0246
private company	1.0	2.0	2.,00	1.0210



External experts from national labs	1.0	5.0	2.600	.9893
External experts from academia	1.0	5.0	2.658	1.0012
Within R&D division	1.0	5.0	3.772	.9442
Within engineering	2.0	5.0	3.629	.8310
Within business management	1.0	5.0	3.275	.8324
Within operation management	1.0	5.0	2.949	.9408
Within marketing	1.0	5.0	3.136	.9193
Cross functional team	1.0	5.0	3.330	.9353
Outsourcing to a consulting firm	1.0	5.0	2.546	1.0307
Outsourcing to academia	1.0	4.0	2.371	.9793
Outsourcing to national labs	1.0	4.0	2.296	.9297
Separate technology forecasting	1.0	7.0	2 (22	
unit	1.0	5.0	2.633	1.1694
Newsletters	1.0	5.0	2.859	1.0741
Magazines	1.0	5.0	2.942	1.0062
Conference proceedings	1.0	5.0	3.422	1.0048
Technical reports	1.0	5.0	3.577	1.0112
Research journals	1.0	5.0	3.396	1.1067
Patents	1.0	5.0	3.196	1.2155
Internal technical data	1.0	5.0	3.816	1.0094
External experts opinions	1.0	5.0	3.318	.9964
Internal experts opinions	2.0	5.0	3.969	.8533
Intuitive decision of top managers	1.0	5.0	3.415	1.0017
Internal market data	1.0	5.0	3.484	1.0025
External market data	1.0	5.0	3.472	1.0269
Vendors input	1.0	5.0	3.042	1.0175
Customers input	1.0	5.0	3.863	.9723
Trend extrapolation	1.0	7.0	4.040	2.2300
Growth curves; S-curves, BASS			2 420	2.1.10
model	1.0	7.0	3.430	2.1449
Bibliometrics; Scientometrics	1.0	7.0	1.980	1.5721
Data mining; Text (Data) mining	1.0	7.0	4.627	1.9455
Growth analogies; Comparison-	1.0	7 .0	2.220	2.0650
based prediction	1.0	7.0	3.238	2.0679
Cross impact analysis	1.0	7.0	2.712	1.9644
System dynamics	1.0	7.0	2.675	1.9716
TFDEA	1.0	7.0	1.984	1.6000
Agent-based model	1.0	7.0	2.222	1.6706
Relevance trees	1.0	7.0	2.582	1.9758
Analytic Hierarchy Process (AHP),				
Analytic Network Process (ANP),	1.0	7.0	2.113	1.7447
Multi-Criteria methods				
Morphological analysis	1.0	7.0	1.971	1.6776
Backcasting	1.0	7.0	2.253	1.7813
Delphi	1.0	7.0	2.313	1.8152
Nominal Group Technique (NGT);	1.0	7.0	3.899	2.4267
1 1 ())				



Brain storming				
Scenario planning / writing	1.0	7.0	4.350	2.3242
Trend impact analysis	1.0	7.0	4.033	2.2825
Technology roadmapping	1.0	7.0	5.415	2.0814
Focus group interview	1.0	7.0	4.983	1.9592
Satisfaction with the results of TF	.0	7.0	4.051	1.5188
The usefulness of TF on	1.0	7.0	4.710	1.4321
technology planning	1.0	7.0	4.710	1.4321
R&D Investment	.0	7.0	4.469	2.0030
Fundamental or basic research	1.0	10.0	2.303	1.9093
Applied research	1.0	10.0	4.070	2.2838
Development	1.0	11.0	5.111	2.6903
Sales growth	1.0	7.0	5.296	1.3411
Return on assets (ROA)	1.0	7.0	4.966	1.2231
Earnings growth	1.0	7.0	5.142	1.2630
Market share	1.0	7.0	5.135	1.2675
Your competitiveness	1.0	7.0	5.306	1.2199



Appendix D. Glossary of Conceptual Terms

Term	Definition
Basic research	Experimental or theoretical work undertaken primarily to acquire knowledge related to disruptive product/process or service
Applied research	Original investigation undertaken to acquire knowledge directly related to next generation product/process or service
Development	Systematic work or practical research for new applications/discoveries related to the current product/process or service
Market Forecasting	It projects the future numbers, characteristics, and trends in your target market
Technology Forecasting (three to five years)	It projects the invention, characteristics, dimensions, or performance of a machine serving some useful purpose within three to five years
Technology Forecasting (over five years)	It projects the invention, characteristics, dimensions, or performance of a machine serving some useful purpose over five years
Technology Planning	It lets an organization know where they are now and where they want to be some time in the future with regard to the technology and infrastructure in their organization
Short-term Forecasting (less than one year)	It covers short term objectives less than one year for example material requirement planning, scheduling, budgeting etc.
Annual Planning	It covers an organization's financial plan for the fiscal year
Action Planning or Operational Planning (one to three years)	It presents highly detailed information specifically to direct people to perform the day-to-day tasks required in the running the organization within three years. It plans the implementation of strategies contained within the strategic plan
Strategic Planning (three to five years)	It sets a direction for the organization, devises goals and objectives and identifies a range of strategies to pursue so that the organization might achieve its goals in targeted market within three to five years
Long-range Planning (over five years)	It aims at formulating a long-term plan, to meet future needs estimated usually by extrapolation of present or known needs over five years. It generally includes short-term (operational or tactical plans) for achieving interim goals

