MIS Quarterly

SPECIAL ISSUE

MAKING SENSE OF TECHNOLOGY TRENDS IN THE INFORMATION TECHNOLOGY LANDSCAPE: A DESIGN SCIENCE APPROACH[1]

By: **Gediminas Adomavicius**
Information and Decision Sciences and MIS Research Center
Carlson School of Management
University of Minnesota
321 19th Avenue South
Minneapolis, MN 55455
U.S.A.
gedas@umn.edu

Jesse C. Bockstedt
Information Systems and Operations Management
School of Management
George Mason University
4400 University Drive
Fairfax, VA 22030
U.S.A.
bockstedt@gmail.com

Alok Gupta
Information and Decision Sciences and MIS Research Center
Carlson School of Management
University of Minnesota
321 19th Avenue South
Minneapolis, MN 55455
U.S.A.
alok@umn.edu

Robert J. Kauffman
Center for Advancing Business through Information Technology
W. P. Carey School of Business and School of Computing and Informatics
Arizona State University
Tempe, AZ 85257
U.S.A.
rkauffman@asu.edu

[1]Sandeep Purao was the guest associate editor for this paper.

Abstract

A major problem for firms making information technology investment decisions is predicting and understanding the effects of future technological developments on the value of present technologies. Failure to adequately address this problem can result in wasted organization resources in acquiring, developing, managing, and training employees in the use of technologies that are short-lived and fail to produce adequate return on investment. The sheer number of available technologies and the complex set of relationships among them make IT landscape analysis extremely challenging. Most IT-consuming firms rely on third parties and suppliers for strategic recommendations on IT investments, which can lead to biased and generic advice. We address this problem by defining a new set of ***constructs*** *and* ***methodologies*** *upon which we develop an* ***IT ecosystem model****. The objective of these artifacts is to provide a formal problem representation structure for the analysis of information technology development trends and to reduce the complexity of the IT landscape for practitioners making IT investment decisions. We adopt a* ***process theory*** *perspective and use a combination* *of **visual mapping** and **quantification** strategies to develop our artifacts and a state diagram-based technique to represent evolutionary transitions over time. We illustrate our approach using two exemplars: digital music technologies and wireless networking technologies. We evaluate the utility of our approach by conducting in-depth interviews with IT industry experts and demonstrate the contribution of our approach relative to existing techniques for technology forecasting.*

Keywords: Design science, IT ecosystem model, IT landscape analysis, management of technology, technology evolution, IT investment

Introduction

The information technology landscape is in a constant state of change. An overwhelming number of information technologies are available for use by organizations and that set continues to grow. Additionally, the economic scope of IT investments can be substantial. Inappropriate IT investment decisions can, therefore, have major adverse effects on organizational performance. These factors contribute to the difficulty of making IT investment decisions. Our discussions with IT managers also indicate that it is difficult to accurately forecast advances and trends in IT. Nevertheless, IT investment decisions must be made. Senior managers must understand the nature of technological change and be able to accurately interpret the IT landscape[2] to position their firms' high-value technology investments and to achieve success with emerging market opportunities.

The following quote from the vice president of global IT infrastructure at a Fortune 500 company shows a typical response to this problem—outsourcing the IT landscape analysis along with the IT strategic decision-making process to third parties:

> *It's kind of a funny thing. In IT it's okay to outsource your future decision-making, but with the business you would never do that...[Companies] outsource their IT decision making just because it's so complicated.* – Vice President of Global IT Infrastructure at a Fortune 500 company

[2]Throughout the paper we often use the terms *IT landscape* and *IT ecosystem*. IT landscape is commonly used by practitioners to describe the overall IT environment. IT ecosystem is a term that we operationally define as a portion of the IT landscape centered on a specific set of technologies in a specific context that is the subject of analysis using the methods and artifacts that we will shortly propose.

The difficulty lies in the need for skills and expertise beyond the capabilities of most firms. As a result, many firms rely on reports produced by consulting companies such as Gartner, Forrester, and IDC, and advice provided by their existing IT partners and suppliers. We recognize that such input can be helpful in the decision-making process; however, our in-depth interviews with IT experts identified two key concerns with this approach. First, advice provided by existing partners and suppliers is often biased; existing suppliers have an incentive to encourage firms to continue their investment. Second, reports produced by third parties are usually too general and often lack formal analysis of the IT landscape, relying primarily on expert opinion and simple extrapolations to make recommendations.

> *The main challenge is the dynamic nature of the whole rapidly changing IT environment...what we need are more formal frameworks and tools to help see more clearly the current and potential future technology landscapes. There is definitely room for improvement in developing these types of tools for managers.* – Senior Academic Researcher and IT Industry Consultant

To address these problems, we propose a new theory-based conceptual approach, a set of new constructs, and a novel methodology for formally analyzing the IT landscape and identifying trends in IT evolution. Adomavicius et al. (2007) proposed a new *ecosystem model* of technology evolution for understanding the dynamic and complex nature of technological evolution. Building on this model, we use a *process theory approach* (Langley 1999; Mohr 1982) to develop a new set of problem representation constructs and a novel methodology for identifying and visualizing patterns of technology evolution in the IT landscape. We extend prior work in this research stream by going beyond the typical use of ecosystems merely as an analogy and developing a new set of analytical tools that aid practitioners in evaluating technological change. The goal of our new approach and methodology is to complement existing techniques and provide firms that make IT investment decisions with a more formal technique for analyzing specific IT ecosystems, making sense of the interdependent relationships among the technologies they contain, and aiding in IT trend prediction.

We adopt a design science research approach (Hevner et al. 2004; March and Smith 1995). *Design science* research involves the construction and evaluation of IT artifacts, constructs, models, methods, and instantiations, by which important organizational IT problems can be addressed. Our proposed set of *artifacts* includes constructs and a *model* for representing relationships between IT components, products, and infrastructure, and a new *method* for identifying and representing patterns of technology evolution. Together, they constitute a novel process for representing, understanding, evaluating, and forecasting the IT landscape, thus enabling managers to make more effective IT investment decisions. As noted by Benbasat and Zmud (2003), the information systems research discipline includes the development of methodological practices and capabilities involved in the planning, construction, and implementation of IT artifacts. This research follows in that vein by providing a new set of tools for analysts involved in the IT investment and development decision-making process.

An important aspect of design science research is the evaluation of the proposed artifacts; in other words, the utility of the proposed artifacts must be demonstrated. To perform this evaluation, we first present two cases to establish validity of the proposed constructs and methods and demonstrate their use in characterizing specific IT ecosystems and IT evolution. We then assess the use of the proposed constructs and methods through in-depth semi-structured interviews with a set of knowledgeable IT industry experts including senior IT executives, consultants, industry research analysts, and academic researchers. These interviews were conducted to provide (1) further understanding and motivation for the business and organizational IT problem we address, (2) an evaluation of the utility of our proposed approach in real-world settings, and (3) suggestions for improvements and future work.

The remainder of the article proceeds as follows. The next section reviews the conceptual foundations of the research and discusses sensemaking from process data and the IT ecosystem model. The third section outlines the new problem representation structure and defines our analytical constructs, including the concepts of IT ecosystem, technology roles, technology paths of influence, and patterns of technology evolution. In the fourth section, we present a state-diagram-based visualization approach for representing trends in IT evolution and illustrate the application of the constructs with a qualitative example from the digital music industry. The fifth section further demonstrates the application of the constructs with a quantitative analysis of the wireless networking IT ecosystem using a new empirical method for identifying trends in IT evolution. The sixth section provides an evaluation of the utility of our proposed approach using in-depth interviews with IT industry experts and an analysis of complementarities with existing techniques for technology forecasting. The final section provides a summary of contributions and limitations of our work as well as opportunities for future research.

Conceptual Foundations

Decision-making and justification for IT investments are of strategic importance for modern firms and can be difficult for even the most-seasoned and knowledgeable managers in the presence of technological, organizational, and market complexity (Bacon 1992; Clemons and Weber 1990). An important aspect of the IT investment decision-making process is analyzing the market landscape to identify and predict trends in IT development, which is often helpful for investment planning and product development strategies. Formal analysis in this domain has traditionally been difficult, primarily due to the sheer number of available technologies and the complex inter-relationships among them. Compounding this problem is the fact that practitioner knowledge of the historical drivers, relationships, and patterns of technology evolution is often limited, and rarely is it well-structured outside the realm of the IT forecasting and consulting firm "gurus." The objective of our research is to address this problem by providing industry practitioners with a new set of tools for analyzing the IT landscape and predicting IT trends. We use existing theory on technology evolution and IT innovation and use a *process theory* approach to guide the design of the constructs upon which we formulate and develop our proposed tools.

The Process Theory Perspective for Design Science Research

Understanding the complexity and changes that occur over time in the IT landscape requires *sensemaking* (Weick 1979) of an environment that consists of many technologies and relationships. *Process theories* are concerned with explaining how complex outcomes evolve or develop over time (Markus and Robey 1988; Mohr 1982), and, therefore, provide the ideal lens for developing tools to analyze the IT landscape.

The process theory approach has been used extensively in IS research, most notably as a base for *structuration analysis* (Orlikowski 1993; Orlikowski and Robey 1991) and for modeling sequences of events (Abbot 1990; Newman and Robey 1992). In many cases, the process theory approach was applied to inform the development of new techniques for analyzing complex process data. Process data are difficult to analyze and manipulate because they deal mainly with sequences of events, often involve multiple levels and units of analysis, vary in terms of temporal precision and duration, and tend to focus on eclectic phenomena such as changing relationships (Langley 1999). This description matches the type of data available to analyze and predict trends in an IT landscape—event data (e.g., new technology introductions) consisting of multiple types of technologies with differing attributes and various measures of time. Our tools should be designed to help practitioners understand how technologies evolve over time and why they evolve in a certain way, which is also a key objective of process-data-related research (Van de Ven and Huber 1990).

Langley (1999) outlines seven strategies for sensemaking and theorizing with process data, and our current research uses a combination of two of them—the *quantification strategy* and the *visual mapping strategy*—to develop the proposed artifacts. The quantification strategy, as exemplified by the research of Van de Ven and Poole (1990), involves the systematic coding of events according to predetermined characteristics. It further involves gradually reducing the complexity of the process data to a set of quantitative time series that can be analyzed using empirical methods (e.g., Garud and Van de Ven 1992; Romanelli and Tushman 1994). The visual mapping strategy, which can be used for the development and verification of theoretical ideas, involves producing graphical representations of process data to present large quantities of data in relatively little space (Miles and Huberman 1994). Visual mappings allow simultaneous representations of a large number of dimensions and can be easily used to show precedence, parallel processes, and the passage of time (Langley 1999). The representations it produces can help researchers (and in our case, managers) look for common sequences of events, patterns, and progressions in process data (Langley and Truax 1994). A common use of visual mapping strategy is the development of process maps, as demonstrated by both organization researchers (e.g., Meyer 1991; Meyer and Goes 1988) and decision science researchers (e.g., Mintzberg et al. 1976; Pentland 1995).

Our research combines the principles and sensemaking strategies of process theory with the formal guidelines of design science research (Hevner et al. 2004) to develop new tools for modeling, visualizing, analyzing, and predicting trends in the IT landscape. The quantification strategy is used for coding IT innovations and developing a methodology for empirically identifying patterns of technology evolution. The visual mapping strategy is used to represent these patterns over time.

The Technology Ecosystem

An *ecosystem view* is a useful approach for representing the many technologies and relationships that make up the IT landscape. Hannan and Freeman's (1977, 1989) seminal work on *organizational ecology* has sparked the increased use of an ecological analogy in business and organization research. The theoretical perspective of organizational ecology is used to examine the environment in which organizations compete as well as the birth and death processes of firms. Strategy researchers have also adopted an ecosystem model in the analysis of business relationships and strategic decision-making (Iansiti and Levien 2002, 2004). Managers and academicians are recognizing the value of the ecosystem metaphor for understanding the complex network of business relationships within and across industries (Harte et al. 2001). Most recently, IS researchers have also begun to adopt an ecosystem perspective: Quaadgras (2005) used network modeling techniques to define the RFID business ecosystem and forecast firm participation, Nickerson and zur Muehlen (2006) analyzed Internet standards creation using a population ecology model, and Funk (2007) presented a hierarchy of relationships between technologies to determine the timing of dominant technology designs.

Although the ecosystem view is proving to be important in business and research, in most cases the ecosystem perspective has been used merely as means of starting discussion. There has been a lack of development of analytical tools that provide real value to practitioners based on an ecological perspective. Additionally, previous research incorporating the ecosystem analogy has focused primarily on industrial ecosystems and relationships between firms and organizations. Our research goes beyond this existing literature in an effort to formalize the ecosystem analogy in the context of IT and apply it to the task of forecasting IT trends.

Two recent papers on IT innovation and technological change provide insights for developing an IT ecosystem model. Lyytinen and Rose's (2003) model of disruptive IT innovation considers the *interrelationships* among technological innovations at the systems development, IT base, and IT service levels. They argue that existing IT innovation theory must be expanded upon, and modeling cross-level impacts of innovation is one of the key steps in understanding the relationships among different technologies over time. In their analysis, they take a primarily organizational innovation view, which demonstrates the effects of disruptive IT innovation on the firm's adoption and acceptance of new technologies. Our research differs by focusing on the technology level of analysis and considering relationships between technologies and technological innovation independent of specific firms. Adomavicius et al. (2007) explored an *ecosystem* approach to technology evolution for the purposes of representing temporal relationships among technologies. Although both of these papers provide useful frameworks for viewing relationships among technologies in the IT landscape, they both stop short of providing useful tools for practitioners and researchers. We attempt to address this gap by using the insights from this prior research to inform the design of our formal modeling constructs and methods, with the goal of producing useful tools to aid IT decision makers in identifying, analyzing, and predicting trends in the IT landscape.

The term *technology ecosystem* emphasizes the organic nature of technology development and innovation that is often absent in standard forecasting and analytical methods. The traditional notion of an "ecosystem" in biological sciences describes a habitat for a variety of different species that coexist, influence each other, and are affected by various external forces. In the ecosystem, the evolution of one species affects and is affected by the evolution of other species. By considering the technology ecosystem as an interrelated set of technologies, a manager can more successfully identify factors that may impact innovation, development, and adoption of new technologies—and ultimately the success of the business activities that use the innovations.

The *ecosystem model of technology evolution* (Adomavicius et al. 2007) integrates the strengths of many modeling methods and theoretical frameworks in economics, engineering, and organizational theory. Three key research streams are combined to provide a comprehensive conceptual model of evolution within a technology ecosystem. First, the *population perspective* (Saviotti 1996; Saviotti and Metcalfe 1984) proposes that multiple interrelated technologies should be viewed as a system or population whose characteristics and members change over time. This concept of viewing technologies as an interrelated system is also supported by Dosi's *technology paradigms* (1982), Nelson and Winter's *technology regimes* (1982), Laudan's *technology complexes* (1984), and Sood and Tellis' *platform of innovation* (2005). Second, complex systems of technologies can be organized in *hierarchies* (Clark 1985; Rosenkopf and Nerkar 1999), which leads to the definition of specific roles played by technologies in the ecosystem. Three levels of the hierarchy are typically considered: *component-level technologies* combine to form *product-level technologies*, and products are then grouped to form a *system of use*. Coevolution of technologies in this model occurs both within and across levels in the hierarchy (Campbell 1990; Rosenkopf and Nerkar 1999). Finally, technologies tend to follow specific *trajectories* (Dosi 1982) and *patterns of innovation* (Sahal 1981, 1985) through the process of technology evolution. Baldwin and Clark (1997, 2000) argue that, in the "age of modularity," specific design rules govern the common patterns of technological innovation. This suggests that patterns and trends in IT innovation can be identified.

Each of the aforementioned research streams (i.e., technology populations, technology hierarchies, and technology trajectories) provides a different (and perhaps complementary) perspective for understanding technological change and has its advantages and limitations. Thus, one of the major contributions of our work is the synthesis of these different research perspectives to develop constructs and methods leading to a more comprehensive understanding of technology evolution.

Model and Constructs

The core of our model is the concept of an IT ecosystem and a set of roles and relationships that are used to code technology innovations and represent patterns of technological change. In this section, we discuss our use of theory to support the design of artifacts (Gregor 2006) and define constructs that provide foundations for a new visual representation and empirical approach for modeling technology evolution patterns over time.

IT Ecosystem

The size and complexity of the IT landscape contributes to the difficulty of predicting future IT developments. To reduce this complexity, we introduce the concept of an *IT ecosystem*. Following the notions of *systems of use* (Rosenkopf and Nerkar 1999) and *technology ecosystem* (Adomavicius et al. 2007), we define an IT ecosystem as a subset of information technologies in the IT landscape that are related to one another in a specific context of use. There can be many different IT ecosystems, which can also possibly overlap. A specific context of use is necessary to be able to define the most relevant set of technologies that make up an IT ecosystem. For example, an IT ecosystem could be defined by an analyst working for a mobile phone manufacturer interested in the context of providing mobile entertainment to users. This ecosystem would include the technologies involved in the delivery and consumption of mobile-phone-based entertainment. By limiting the scope of an ecosystem through the context of use, the complexity of the IT landscape is greatly reduced, and trends relevant to the analysis at hand can be more easily identified.

Roles in the IT Ecosystem

The hierarchical nature of technologies within a population leads to the identification of specific *roles* that technologies can play within an IT ecosystem. By acting through these roles, classes of technologies can influence each others' evolution and development through common patterns of innovation. Due to the systemic nature of IT, information technologies can act as *products and applications*, *components*, or *infrastructure* (Adomavicius et al. 2007).

The *product and application role* describes technologies that interact with a user in the given context of use and are built up from component technologies. They are designed to perform a specific set of functions in the specific context of use. For example, in an IT ecosystem centered on digital music playback, an MP3 player would act in a product role because it interacts directly with the user in the given context: storing and playing digital music files. Other technologies that would be considered products in this context include CD players, mobile phones, laptops, and satellite radio devices.

The *component role* represents technologies that are subunits or subsystems of other technologies in an IT ecosystem. For example, in a personal computing IT ecosystem, there are several technologies that act as components: microprocessors, RAM chips, hard disk drives, etc. Individually and in combination, these components provide functionality to products (such as laptops, desktops, PDAs, and smart phones) in this IT ecosystem. The concept of component is very closely related to *module* as defined by Baldwin and Clark (2000). To differentiate between components and products, the latter are typically defined by designers and emerge by combining components into products that solve users' problems or needs. For example, a recent report on emerging economies notes that combining existing components to create new products is becoming a common mode of technological innovation (*Economist* 2007). Individual component technologies can be subunits of multiple products in the same ecosystem and contain components themselves. For example, the hard disk drive is a standard component in many of the products mentioned above. However, the hard disk drive also has a set of component technologies itself, including DC spindle motors, actuators, and platters. This emphasizes the importance of defining the scope of the IT ecosystem around a context of use relevant to a specific analytical task.

The *infrastructure role* describes technologies that enable or work in conjunction with (or as a peripheral to) product and application role technologies in an IT ecosystem. Note that the term *infrastructure* has multiple connotations in the research literature. For example, Star and Ruhleder (1996) define infrastructure as a constellation of products that are in use by multiple communities (over time and space). In this paper, we define infrastructure as technologies that add value to the use of the product technologies they support in the given context of use. Therefore, technologies in the infrastructure role are, by definition, differentiated from product technologies. For example, in the personal computing IT ecosystem, a printer becomes an infrastructure technology because it is not physically necessary for the design and use of a PC, but it extends the PC's functionality, expands the PC's system of use, and provides additional value and services to users.

Paths of Influence in the Technology Ecosystem

Technological evolution and development is complex and can take many paths within a technology ecosystem. Boland et al. (2003) argue that understanding the changes of information technology over time requires an integrated view of the innovation process. In particular, their work highlights the importance of history and the effects of time in understanding innovation (Arthur 1989) and viewing it as a continuous path creation process. To capture the types of temporal influences technologies have on one another, we define *paths of influence* to represent the impacts of innovation across technology roles within an IT ecosystem. Innovations in any one of the technology roles within an ecosystem can cascade through the other roles resulting in subsequent innovations. We are essentially adopting a *path-dependent* view, in which change in an IT ecosystem follows "a dynamic process whose evolution is governed by its own history" (David 2007, p. 1). For example, the introduction of a new component technology can influence the development of new product technologies in the future, representing a specific path of influence: Component role → Product/application role* (or C→P*). Here the asterisk (*) is used to indicate a future state of a technology role in the ecosystem, and C, P, and I are used as abbreviations for component role, product and application role, and infrastructure role.

Paths of influence represent the impact one technology role has on another in the evolution of a set of technologies in the ecosystem. For example, the success of the DVD player has helped drive the development of new DVD component technologies. These include recordable DVD ROMs, multi-layer DVD ROMs, and new blu-ray and HD technologies (P→C*). Similarly, the evolution of infrastructure technologies can drive the development of new product technologies. For example, a third-generation cellular phone network provides infrastructure for new phone services and applications such as streaming video and rich applications (I→P*). Paths of influence provide a problem representation structure for analyzing technological interdependencies in an IT ecosystem over time. Specifically, they provide a way to reduce the complexity of relationships among technologies within an ecosystem and identify trends in technological change. Table 1 presents a

Table 1. Paths of Influence in a Technology Ecosystem

	Component Future State (C*)	Product Future State (P*)	Infrastructure Future State (I*)
Component Present State (C)	**Component Evolution**. Examples: Moore's law and the continual improvement of microprocessor performance.	**Design and Compilation.** Examples: Combining of new touch screen components and hand writing recognition software to create tablet PCs.	**Standards and Infrastructure Development**. Examples: The development of IEEE 802.11 standards for wireless components.
Product Present State (P)	**Product-Driven Component Development**. Examples: New designs for smart phones and PDAs driving development of higher capacity flash-based storage components.	**Product Integration and Evolution**. Examples: Integration of PDA and mobile phone to create the smart phone for personal computing.	**Diffusion and Adoption**. Examples: Widespread adoption of personal computers helps drive high-speed internet service development.
Infrastructure Present State (I)	**Infrastructure-Driven Component Development**. Examples: Internet and broadband infrastructure helps drive development of wireless chipsets and multimedia optimized processors.	**Infrastructure-Leveraging Product Development**. Examples: Internet-optimized PC designs and smart phones designed to utilize the broadband wireless services.	**Support Evolution**. Examples: Continual improvement of networking infrastructure, such as gigabit Ethernet and fiber optics.

3×3 matrix that classifies the nine possible paths of influence based on the three information technology roles. The examples in Table 1 are potential paths of influence in a personal computing IT ecosystem.

There are many theories of what drives technological change. *Technological determinism* posits that technological development drives social and cultural changes (Smith and Marx 1994), while *social construction of technology* (SCOT) argues the opposite: society and culture determine technological development (Bjiker et al. 1987). A related, yet slightly different debate exists in the economics and management literature. On one hand, demand-side forces, such as consumer and market needs, drive technological development (e.g., Adner and Levinthal 2001, Clark 1985, Malerba et al. 1999). The opposing perspective is that supply-side forces, such as firm capabilities and research and development, are responsible for technological development (e.g., Dosi 1982, Sahal 1985). Our current model is focused on the technical drivers of technological change (Nelson 1995) and does not explicitly model external forces such as society, culture, and the supply or demand environment. We recognize that society and culture impact the development and evolution of technology. Clearly, technological determinism and SCOT encompass the set of theoretical perspectives on technology evolution. Both technological and social forces impact the development of technology, and in our theoretical model we assume that the mix of these forces varies by ecosystem and, therefore, is an endogenous factor to our analysis. In an effort to develop a parsimonious model and usable artifacts that reduce the complexity of the IT landscape, our current model is focused only on technology roles and relationships in an IT ecosystem. Although our long-term goal is to incorporate both societal and technological forces and develop a comprehensive set of interactions, in this paper we demonstrate that reducing technological complexity while increasing the understanding of the IT landscape can be accomplished by focusing strictly on relationships among information technologies. Thus, since our model is targeted for use by domain experts, for this study we assume that domain experts are aware of market and social forces and will be able to define their ecosystems with appropriate consideration.

Representing Patterns of Technology Evolution

Identifying patterns of technological change within an IT ecosystem is necessary for predicting future trends. Sahal (1981, 1985) identifies several specific patterns of technological change, including invention, innovation, and diffusion, and recognizes that technology development follows an evolutionary process. Other researchers have made similar observations. Worlton (1998) observes that patterns of technological change typically follow four stages: invention, innovation, diffusion, and change of scale, and Baldwin and

Clark (1997, 2000) argue that, due to increased modularity, specific design rules can lead to predictable innovation patterns. The constructs defined in the previous section can be used to identify patterns of technological change within an IT ecosystem.

Visual mapping strategies provide a means for simultaneously representing multiple dimensions and can help researchers identify common patterns, sequences, and progressions in process data (Langley 1999; Langley and Truax 1994). For example, Nickerson and zur Muehlen (2006) demonstrated the use of a population ecology perspective to map out the complexities in Internet standards making. They use a visual mapping strategy to represent the "space-time network" of the migration of ideas generated during Web services standards development. Similarly, Boland et al. (2003) used a visual mapping strategy to represent path creations in industries as a result of IT-led innovations. We present a method for visually mapping patterns of technological change in an IT ecosystem to help IT practitioners identify, analyze, and predict IT trends using the concepts of technology roles and paths of influence.

As technologies evolve, some new technologies are introduced, and some existing technologies die out. An ecosystem's form and content change as well as the patterns of evolution occurring within the ecosystem. Technologies in an ecosystem can be coded into the roles

- *components* (e.g., technological subunits that can be combined to form higher-level technologies)
- *products* (e.g., technologies that interact with the "user" in a given usage context)
- *infrastructure* (e.g., technologies that support and extend the use of product technologies)

Within a specific time period, the quantity of technologies in each role determines the dominance of a role in the ecosystem. Transitions from one set of dominant roles in the ecosystem to another set can then be represented by paths of influence and, over time, evolutionary patterns can be identified as *collections* of the paths of influence occurring in the IT ecosystem. Table 1 provided a pattern template, and Figure 1 provides examples of several patterns of technological change, each one represented by a collection of paths of influence (denoted by shaded cells) occurring in an ecosystem at the same time.

An alternative representation of the patterns can be achieved using a graph-based approach. The nodes in Figure 2 represent the collection of component (C), product (P), and infrastructure (I) technologies at each time in the evolutionary process. The edges between nodes represent the individual paths of influence, and the evolutionary patterns are represented by the set of edges in each time period.

Three roles may seem to offer a rather simple representation; however, nine possible paths of influence emerge from these roles, and dozens of possible patterns of technology evolution emerge as various combinations of different paths of influence. The three technology roles provide a simple set of constructs that enable representation of a large number of complex patterns of technological change.

Although the ability to identify single patterns of evolution in technology ecosystems provides insights for managers making technology-related decisions, a more significant contribution of the ecosystem model is its ability to provide a systematic approach for describing the temporal changes (transitions) in the ecosystem using these patterns. In the next section, we demonstrate the use of our approach by examining how a series of evolutionary transitions can be represented by connecting multiple patterns over time, which can lead to the identification of some intrinsic patterns that can be utilized in technology forecasting. We also demonstrate how analysts can use educated speculation based on the results of our approach to forecast future patterns of technological change.

Qualitative Application: Evolutionary Transitions in Digital Music Technologies

We use the digital music technology ecosystem to provide a demonstration of a qualitative approach for applying the constructs and identifying patterns of technological change. This example demonstrates the design and use of our constructs and communicates their relevance for both IS research and practice. We use our visual mapping strategy to create a state diagram to map the patterns of technological change and innovations that emerge.

Qualitative Analysis Approach

The digital music technology ecosystem is an ideal setting for analysis. It includes many different component, product, and infrastructure technologies and, although most digital music technologies have only existed since the mid-1990s, there has been a significant amount of technological change in this ecosystem. Demand for these technologies has skyrocketed over the past several years, so we expect to see many new product introductions in the market. Additionally, digital music tech-

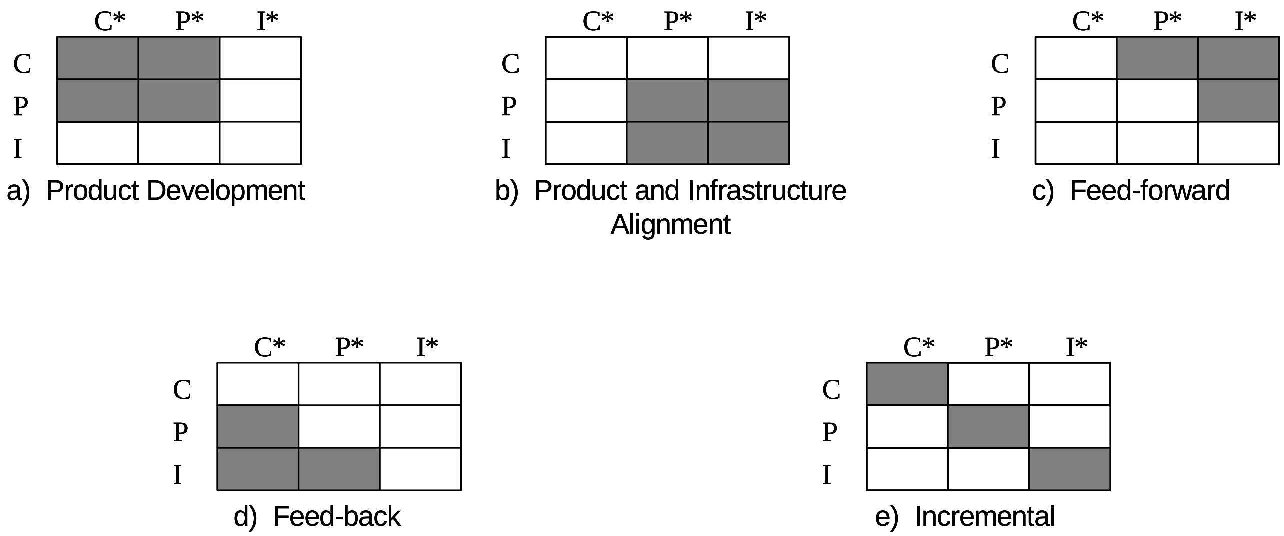

Figure 1. Example Patterns of Technological Change

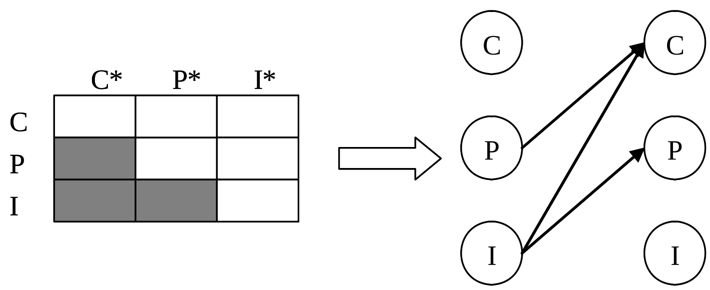

Figure 2. Transformation between Different Pattern Representations

nologies span the consumer electronics, entertainment, and computer industries, which suggest that there is an underlying complexity in their design and relationships within the ecosystem. Furthermore, digital music technologies have revolutionized the consumption of music and other forms of media, and most people can relate to these technologies since they likely own or use them.

In developing this qualitative example, we follow the descriptive approach outlined by Hevner et al. (2004) to demonstrate the application of our proposed constructs. We used LexisNexis and Internet search tools to gather announcements, news stories, and historical records related to technologies in the digital music ecosystem between 1989 and 2006. In total, we gathered information on approximately 100 related technologies (e.g., flash-based storage, LCD screens, MP3 players, digital music services). These announcements were coded into examples of new technologies in the component, product, and infrastructure roles. Using information on the timing of technology releases, we developed a rich qualitative interpretation of technology trends in the ecosystem. We provide insights on the nature of digital music technology evolution and illustrate the use of our artifacts for qualitative analysis of an IT ecosystem.

Technology Evolution in the Digital Music Ecosystem

The demand for digitally formatted music files, players, and services has grown steadily over the past decade. In fact, a new digital music market has developed with many technological innovations and rapid consumer adoption. Since it was originally patented in Germany in 1989, the MP3 audio compression format has had a significant impact on the traditional music industry. In 1999, peer-to-peer (P2P) file sharing networks gained rapid acceptance, sparking legal battles and the development of new encryption and file-tracking technologies. In February 1999, Sub Pop Records became one of the first labels to begin releasing music in the MP3 format (*Wired News* 1999). Since then, the introduction of mass storage digital music players and online digital music retailers has transformed the music business. Table 2 and Figure 3 provide multiple illustrations of the time line and the evolution of digital music technologies.

Digital music technology evolution started with the introduction of the MP3 compression format and software applications for playing MP3-encoded music files. The birth period of the digital music industry was characterized primarily by the initial product development pattern of technology evolution (Figure 1a), where component technologies (such as the MP3 compression format) and product technologies (digital music software, such as WinAmp) were being refined as they gained more attention. Activities in this era included the refinement of the MP3 format by integrating it into MPEG-1 in 1992 and MPEG-2 in 1994. Once MP3 files reached a reasonable level of adoption, a *feed-forward* pattern of technology evolution (Figure 1c) took over as new product and infrastructure technologies were introduced based on the MP3 encryption format. The first portable MP3 player, the 32MB MPMan device from Eiger Labs, was released in mid-1998 (Van Buskirk 2005), and P2P networks were introduced with Napster's inception in May 1999. Both technologies emerged because of the popularity of the MP3 compression format.

As popularity increased for the technologies in the digital music ecosystem, additional infrastructure technologies were developed to align with existing product offerings (Figure 1b), including refinements to P2P networks and the introduction of new digital music encoding standards, such as Microsoft's WMA and Apple's AAC. As a result of the continued growth in popularity of digital music products and technologies, a *feed-back* pattern of technology evolution (Figure 1d) took hold, and new components and products, such as higher capacity flash-storage-based players, were developed. At this point, the majority of MP3 players were flash-storage-based and virtually all MP3 file distribution occurred over P2P networks.

These patterns of technological change repeat themselves with the next generation of digital music technologies. Innovations in components, such as high-capacity micro hard disk drives, led to the initial product development of hard disk drive-based MP3 players, such as the Apple iPod and the Creative Nomad Jukebox. These new HDD-based players sparked a new *feed-forward* pattern of evolution that resulted in the introduction and adoption of new online music services, such as iTunes and Napster 2.0, as well as a slew of accessories for portable MP3 players, such as FM transmitters and voice recorders. With the presence of multiple online music providers and portable MP3 players, technology evolution became focused on the alignment of infrastructure and product technologies. The wide adoption of the second-generation digital music technologies led to feed-back patterns that included introduction of new products using new components such as color LCD screens.

Mapping the Analysis Back to the Constructs

The events that occurred in the digital music technology ecosystem can be represented as patterns of technological change using the roles and paths of influence. Figure 4 provides a visual representation of transitions between multiple evolutionary patterns over time. Coding the technologies into roles allowed us to identify paths of influence, represented by the arrows in Figure 4, and multiple patterns of technology evolution, represented by the collection of arrows in each time period. Figures 3 and 4 represent two different ways in which we can visually depict the sequence of 3×3 matrices representing paths of influence as a state diagram. Both qualitative and quantitative analysis can be used to develop these representations of evolutionary patterns, enabling an analyst to understand and predict the next generation of technologies in the desired context. Our development is supported by prior research, which shows that innovation typically occurs in specific patterns (Baldwin and Clark 2000; Sahal 1981, 1985; Worlton 1998), in some cases cycles (Rosenkopf and Nerkar 1999; Worlton 1998), and that new innovations typically replace existing ones (Rosenkopf and Nerkar 1999).

Based on this visual mapping, an analyst could forecast that the next generation of digital music technologies will begin as new components are introduced that allow for even more advanced features in product technologies. For example, the evolution of components that are used across multiple ecosystems may result in the convergence of hand-held computing devices (e.g., PDAs, cellular phones, MP3 players, digital cameras). In fact, Motorola introduced one of the first MP3-enabled mobile phones (Shillingford 2005), and the Sony/Ericsson Walkman MP3 phone grew sales by 33 percent in the second quarter of 2006 (Ewing and Burrows 2006), as demand expanded in the presence of falling prices. Microsoft released a new multimedia-playing (audio, video, and software) hand-held device called Zune in November 2006, and Apple released its "iPhone," an iPod-phone hybrid device, in mid-2007.

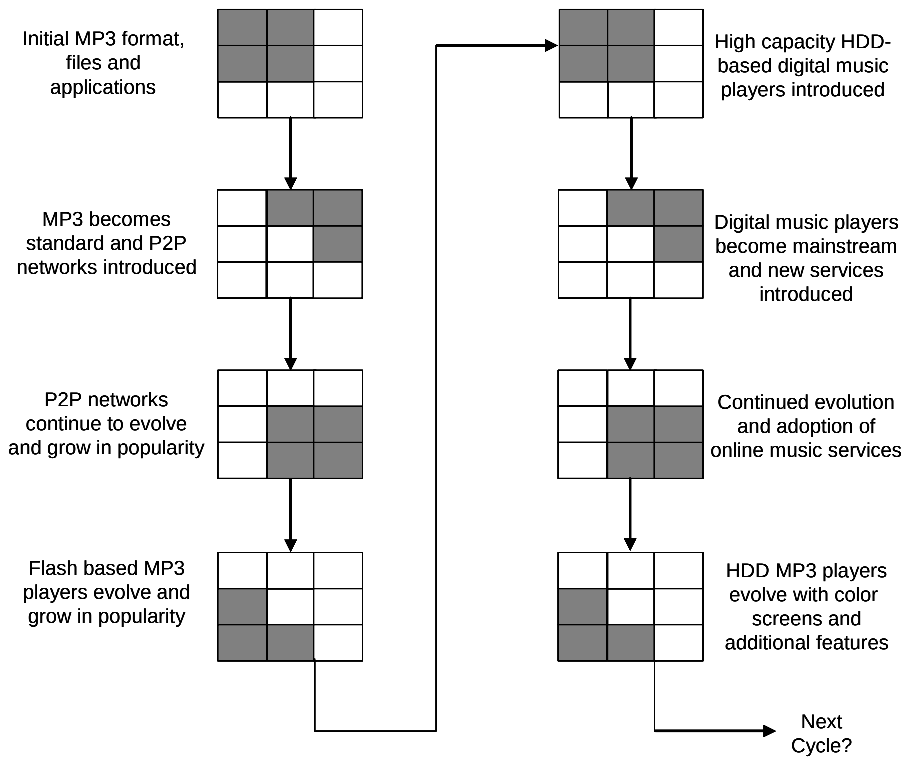

Figure 3. Patterns of Digital Music Technology Evolution

Table 2. Time Line of Digital Music Technologies

Year	Event
1989	German MP3 patent
1996	US MP3 patent
1998	First portable MP3 player (32 MB)
February 1999	Sub Pop distributes MP3 music
May 1999	Napster founded
May 2000	Transactional watermarking developed
January 2001	Apple iTunes music applications released
July 2001	Napster injunction
October 2001	10 GB Apple iPod introduced
March 2002	20 GB iPod for PC introduced
April 2003	40 GB iPod introduced
October 2003	Dell DJ introduced iTunes online music store opens
September 2004	MSN online music store opens
May 2005	Yahoo online music store opens
October2005	First iPod with video capabilities
September 2006	iTunes starts selling full length movies
August 2006	160 GB 1.8 inch HDD introduced
July 2007	iPhone (MP3 player/phone) introduced
September 2007	160 GB Video iPod introduced

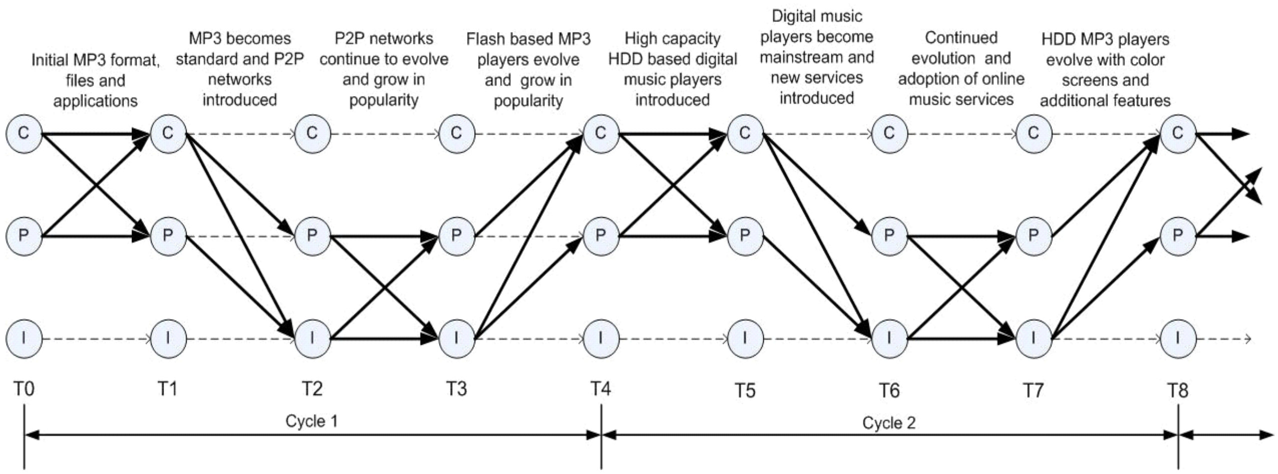

Figure 4. Digital Music Technology Graph-Based State Diagram

Currently the ecosystem is rapidly evolving to include many new technological possibilities, such as embedded digital rights management (DRM), web services on hand-held devices, GPS built-in functionality for location-based shopping, and component innovations that will eventually support mobile TV. The ecosystem view allows the manager to model these types of evolutionary patterns as well as track and analyze their progression over time, which provides better understanding of the dynamic nature of technological change in a given context.

Quantitative Application: Evolutionary Transitions in Wi-Fi Technologies

To further substantiate the application of our constructs and model, we developed a new empirical methodology to identify technology evolution patterns by combining a quantification strategy with the visual mapping state-diagram-based approach for sensemaking from process data (Langley 1999; Van de Ven and Poole 1990). A quantitative approach for analyzing the IT landscape provides a strong complement to the qualitative approach we demonstrated in the previous section. When sufficient data on the introduction of technologies are available, a quantitative approach provides additional rigor to the identification of evolutionary patterns. We follow guidelines in Hevner et al. (2004) and use an analysis of real data to demonstrate our methodology.

Data

The wireless networking ecosystem provides an appropriate context for applying our empirical methodology for several reasons. Similar to the digital music technology ecosystem example, wireless networking technologies are relatively young but have experienced a large amount of technological change; in addition, these technologies also fit into the computer and consumer electronics industries, so complexity is high. However, unlike digital music technologies, wireless networking technologies have had clearly defined generations based on IEEE standards. The existence of these standards suggests that recognizable patterns may exist, and our empirical methodology can be validated by identifying those patterns. Furthermore, wireless networking technologies are used not just by individuals but also by firms and organizations. They are also typically certified by the Wi-Fi Alliance, which maintains a database of product certifications and makes the data publicly available.

> *The Wi-Fi Alliance is a global, non-profit industry trade association with more than 300 member companies devoted to promoting the growth of wireless local area networks (WLAN). Our certification programs ensure the interoperability of WLAN products from different manufacturers, with the objective of enhancing the wireless user experience.* (www.wi-fi.org)

This provides an opportunity to compare and contrast different ecosystems, and to evaluate our constructs and visual mapping strategy with both qualitative and quantitative analyses.

We collected data on over 3,000 certifications for new wireless networking (802.11) technologies awarded by the Wi-Fi Alliance. The member companies of the Wi-Fi Alliance include 3Com, Apple, Dell, Intel, Linksys, and many others. Certifications are awarded for 10 different technology categories: access points, cellular convergence products, compact flash adapters, embedded clients, Ethernet client devices, external cards, internal cards, PDAs, USB client devices, and wireless printers. Technologies can be certified based on IEEE communication standard (802.11a, b, g, d, and h), security (e.g., WPA, and WPA2), authentication protocol (e.g., EAP, and PEAP), and quality of service (e.g., WMM).[3]

Generally, historical product data that includes comprehensive technical specifications and dates of release is difficult to obtain. However, the Wi-Fi Alliance certifications have been awarded to a substantial number of technologies, with most certified prior to their commercial release. For this reason, we have used the date of certification as a proxy for the date of innovation for a new technology, and the type of certification as a proxy for the technical specifications of the product. Both are readily observed, and the former is likely to occur close to the date of innovation, and so they represent acceptable empirical proxies.

We coded the Wi-Fi certification categories into the ecosystem roles (component, product, and infrastructure) based on our operationalization the IT ecosystem model. Compact flash adapters, internal cards, external cards, and USB client devices were coded as component technologies, because each clearly acts as a component by providing wireless capabilities for product devices. We coded access points, Ethernet client devices, and wireless printers as infrastructure, because these technologies either form or extend the network infrastructure necessary for wireless communication. Finally, we coded PDAs, embedded clients (PCs and laptops), and cellular convergence technologies (Wi-Fi enabled cell phones) as products, because each represents a product device that provides fully functioning wireless networking capabilities to the end user. Coding the wireless technologies into appropriate roles leads to the identification of dominant roles and the paths of influence between roles. The collections of these paths of influence at different time periods represent patterns of technology evolution in the ecosystem.

Empirical Methodology

Following a quantification strategy similar to Van de Ven and Poole (1990), we present a methodology for reducing the complexity of technology evolution process data to a set of time-based quantitative data that can be used to empirically identify patterns. Table 3 provides a high-level description of the steps in the methodology.

First, raw technology introduction data were coded according to the component, product, and infrastructure roles within a specific ecosystem (Step 1 in Table 3). As noted above, the wireless networking data were coded based on the product category assigned to a technology in the Wi-Fi Alliance certification. Technical specifications for wireless networking technologies exhibit a natural progression over time. For example, the IEEE 802.11b standard was introduced prior to the 802.11g standard and, therefore, new technology introductions are distributed accordingly, based on their technical specifications. We use the technical specifications of the IEEE communication standard (802.11b versus 802.11g) and the basic security standard (WPA1 versus WPA2) to identify different generations of wireless technologies. We independently analyzed each 802.11 and WPA generation (i.e., two generations in each category) and then made comparisons across generations to identify patterns of technology evolution.

Next, to derive a baseline for the number of new technologies introduced over time, we estimated a function of the frequency of all technologies introduced across all roles (Step 2 in Table 3). This function provides an approximation for the total innovation activity in the technology ecosystem over time. A wide variety of approximation techniques may be used for this purpose. For example, for the wireless network data we used a 5-month moving average of the frequency counts (i.e., to eliminate random monthly fluctuations and obtain the underlying trend) and estimated the frequency curve using a polynomial approximation function. In this specific case, a sixth-degree polynomial provided a good fit with R^2 values over 90 percent. Figure 5 depicts the estimation for the frequency of technology introductions in the 802.11b generation.

[3]WPA (Wi-Fi protected access) is a standard for wireless network security. For more information, see en.wikipedia.org/wiki/WPA. EAP (extensible authentication protocol) is a universal authentication framework frequently used in wireless networks, and PEAP is an open-standard authentication framework based on EAP proposed by Cisco, Microsoft, and RSA Security. See en.wikipedia.org/wiki/Extensible_Authentication_Protocol for additional information. WMM (Wi-Fi multimedia, also known as WME—wireless multimedia extensions) is a standard that provides basic quality of service (QoS) for wireless networks by prioritizing traffic according to the following access categories: voice, video, best effort, and background. en.wikipedia.org/wiki/WMM offers details.

Table 3. Empirical Methodology Overview	
Step	**Description**
1. Coding	Raw data on technology introductions is coded into the component, product, and infrastructure roles.
2. Frequency Estimation	A function of the frequency of all technology introductions over time is estimated.
3. Threshold Determination	Based on the proportion of technologies of each role within the overall number of technology introductions, a threshold function is derived for each role.
4. Dominant Role Identification	Actual frequency of technology introductions is compared to threshold function for each role to determine dominant roles in each time period.
5. Pattern Identification	Transitions between dominant roles in adjacent time periods are mapped out.

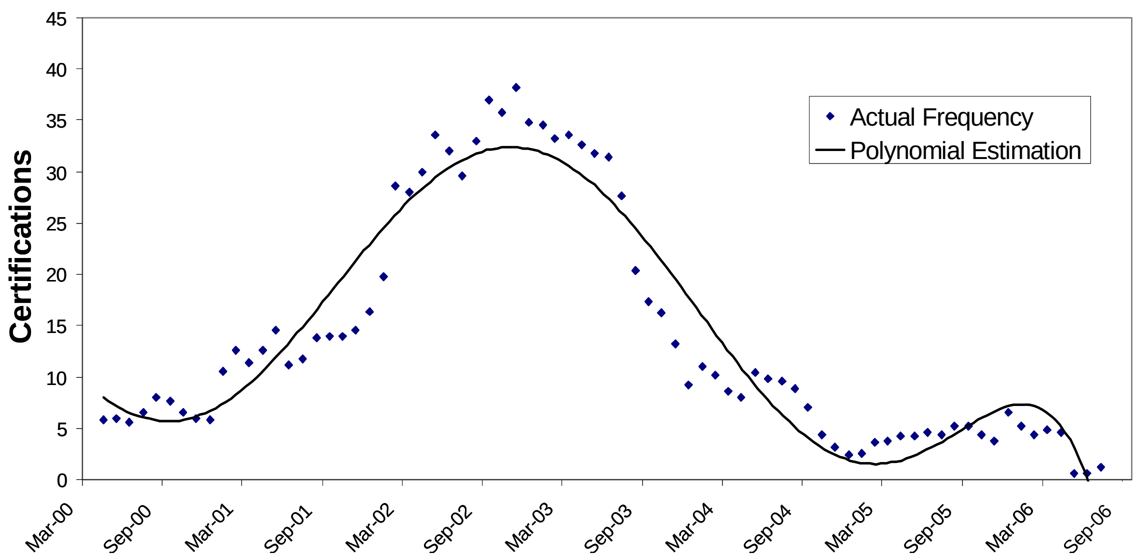

Figure 5. Estimating the Monthly Frequency of 802.11b Technology Certifications Using a Polynomial Approximation Function

We next derived *threshold frequency functions* for each role using the frequency function estimated for all technology introductions (Step 3 in Table 3). If we assume that the technology roles do not have an effect on the timing of new technology introductions and there are no interdependencies across roles, we would expect to see the number of technology introductions in each role over time be proportional to the total number of technology introductions in the ecosystem. With this in mind, we derive estimated frequency functions for each role based on the proportion each role has of the total number of technology introductions. For reference, the set of technologies released in the 802.11b generation is 54.4 percent components, 10.4 percent products, and 35.2 percent infrastructure, and the set released in the 802.11g generation is 45.9 percent components, 8.0 percent products, and 46.1 percent infrastructure. In Figure 6, the top curve represents the estimated frequency function for all technologies and the three curves below represent the proportional frequency estimates for components, infrastructure, and products, respectively from the top.

Estimating the proportional frequency curves is necessary in order to take into account scale differences in the number of technologies introduced in each role. In the context of the wireless networking data, the total number of product certifications is significantly lower than the number of component and infrastructure certifications. There are several possible reasons for the lower number of product certifications. In par-

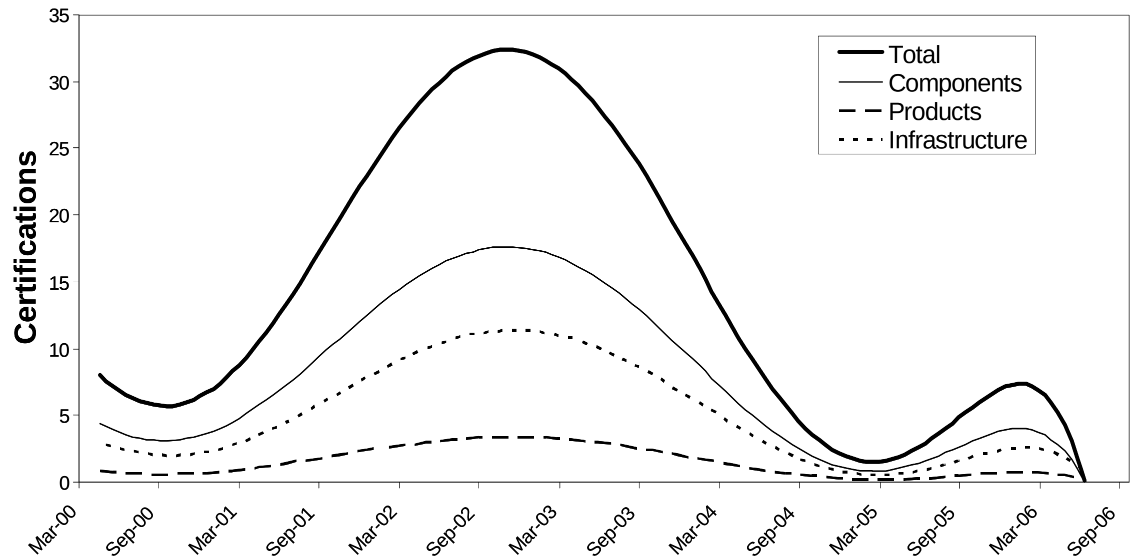

Figure 6. Proportional Frequency Functions for the Total Number of 802.11b Certifications and Each Technology Role

ticular, one certification for an embedded client or cellular convergence technology is often applied to multiple product models using the same technology. For example, Dell may certify one laptop-embedded client and then apply the certification to multiple laptops using the same client. Also, not all product technologies in this ecosystem need to be certified. For example, a laptop that uses a wireless adapter is a product technology in this ecosystem; however, the adapter is certified but not each possible laptop model.

The proportional frequency functions are used as thresholds for determining the dominant technology roles over time (see Step 4 in Table 3). If the number of actual technologies released for a certain role is above (below) the threshold, then one can argue that there is proportionally more (less) innovation activity occurring in that role than expected under the assumption of independent technology introductions and no interdependencies among roles. Using error bars, in this case exogenously set at ±5% of the threshold curve value, actual frequencies of technology introductions in each role are compared to the threshold (plus or minus error) to determine which roles are dominant at what times. Figures 7 and 8 present this comparison for the 802.11b and 802.11g wireless technology generations. In the figures, the solid line with error bars is the threshold curve, the dotted line represents the actual frequency counts per month, and the smoothed line represents a 5-month moving average of the frequency counts. From these plots it is apparent that over time the dominant technology roles vary. For example, for the 802.11b generation it is clear that component and infrastructure technologies either trace the threshold or surpass it for the first half of the generation, but they begin to lag in the second half as product technologies begin to dominate. Similar patterns are apparent in the 802.11g figure.

The results of the threshold comparisons discussed above can be represented using the visual mapping strategy discussed previously. By identifying the dominant technology roles in each time period, a state diagram can be created to represent the transitions across technology evolution patterns (see Step 5 in Table 3). The next section provides the examples of state diagrams obtained from the Wi-Fi certification data using the proposed methodology.

Mapping the Analysis Results Back to the Constructs

Based on the analysis presented in Figures 7 and 8 for the 802.11b and 802.11g wireless technologies, the state diagram in Figure 9 was generated, which allows several general trends to be observed. The empirical method described above identifies the dominant technology type within each time period (represented as nodes in Figure 9), and the expert can then define the transitions from one time period to the next (represented as arrows in Figure 9) using contextual informa-

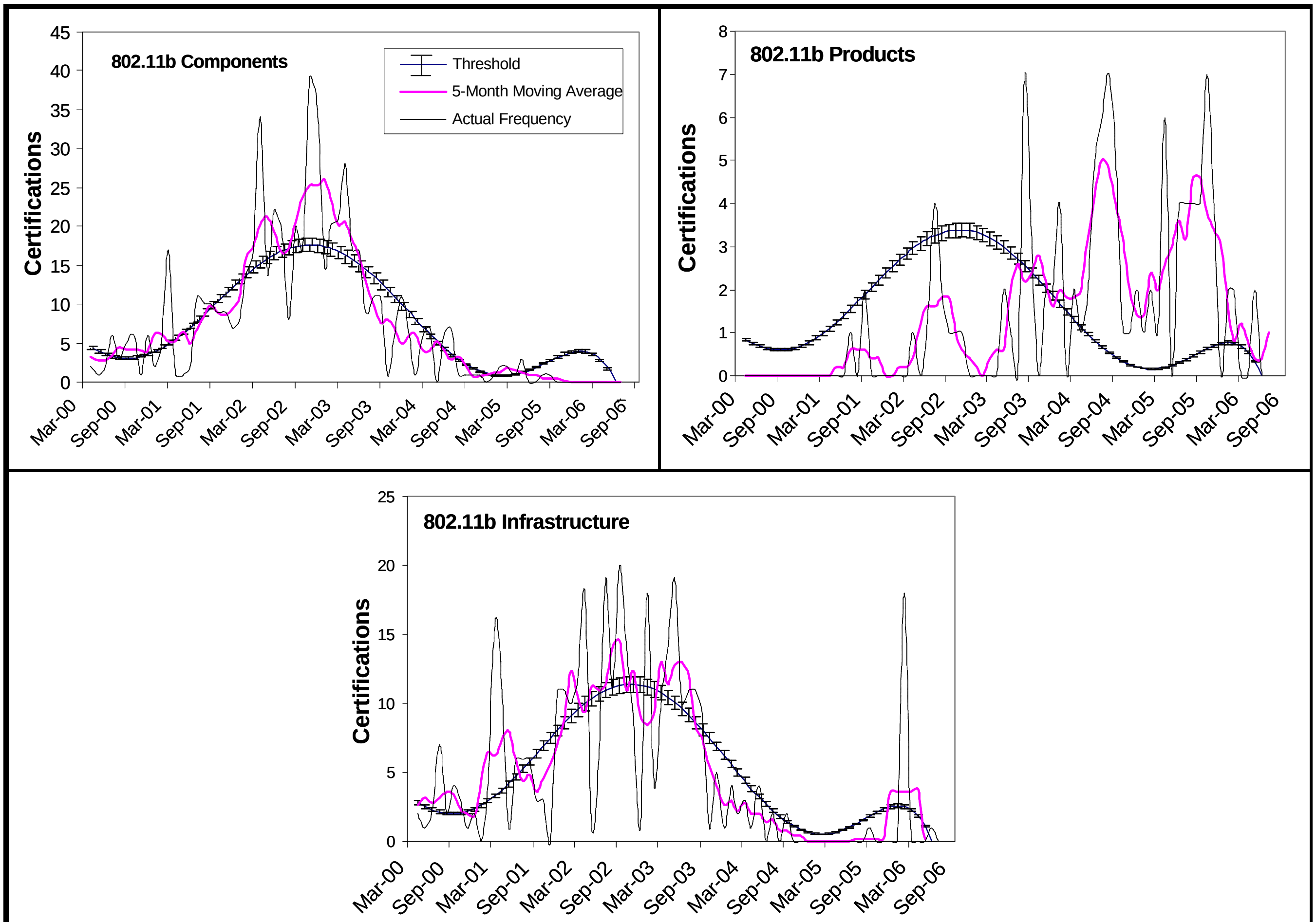

Figure 7. Actual Frequencies of 802.11b Technologies Plotted Against Threshold Functions

tion from the domain. In particular, it is apparent that innovations in product technologies clearly lag the introduction of new component and infrastructure technologies. As 802.11b component and infrastructure innovation intensity begins to drop off, an increase in 802.11b product certifications develops as well as the initial certifications for 802.11g components and infrastructure (i.e., the next innovation cycle begins). In addition, product innovations initially lag component and infrastructure innovations, but for the second generation this lag is shorter, likely because 802.11g products are backward-compatible with 802.11b components and infrastructure. Manufacturers are able introduce the next generation (802.11g) of wireless product technologies more quickly without having to wait for the widespread development of 802.11g components and infrastructure.

A state diagram for the WPA1 and WPA2 generations in the same wireless networking data is presented in Figure 10. In this case, it is also apparent that component technology innovations predate product and infrastructure technology innovations. In the WPA2 generation the progression of technological innovation was from components to infrastructure to products, while in the WPA1 case there is an initial component precedence followed by a dominance of infrastructure and products.

Using the information provided by these two cycles of technology evolution in the Wi-Fi ecosystem, an analyst may be able to forecast that the lag between component and infrastructure technology innovations and product technology innovations will continue to reduce, and eventually simultaneous innovation across all technology roles will occur. In 2006, Linksys demonstrated routers (infrastructure) and Internal cards (components) that operate on the emerging 802.11n standard (Garcia 2006) and Dell Computer shipped an 802.11n laptop client (product) using Broadcom chipsets

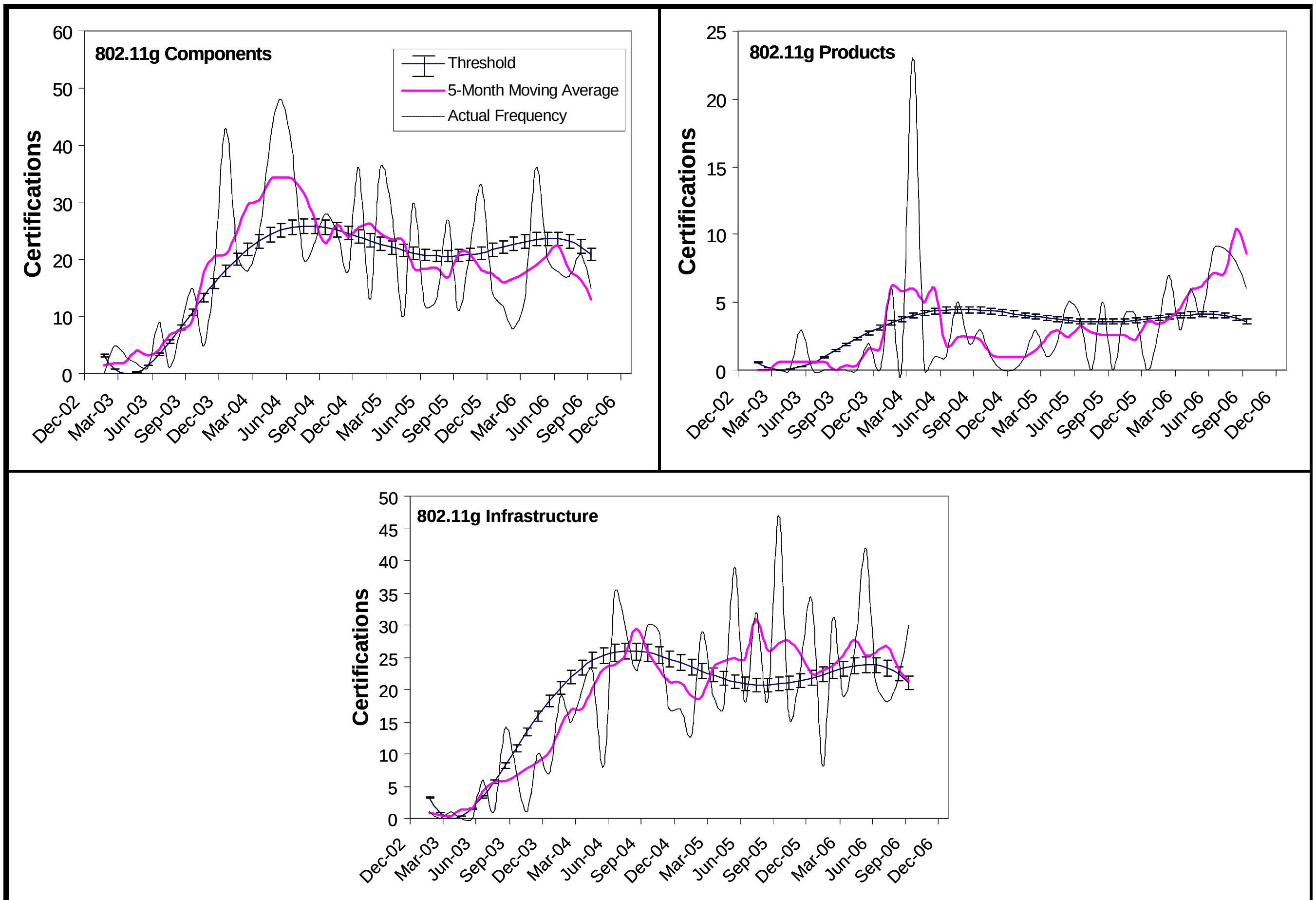

Figure 8. Actual Frequencies of 802.11g Technologies Plotted against Threshold Functions

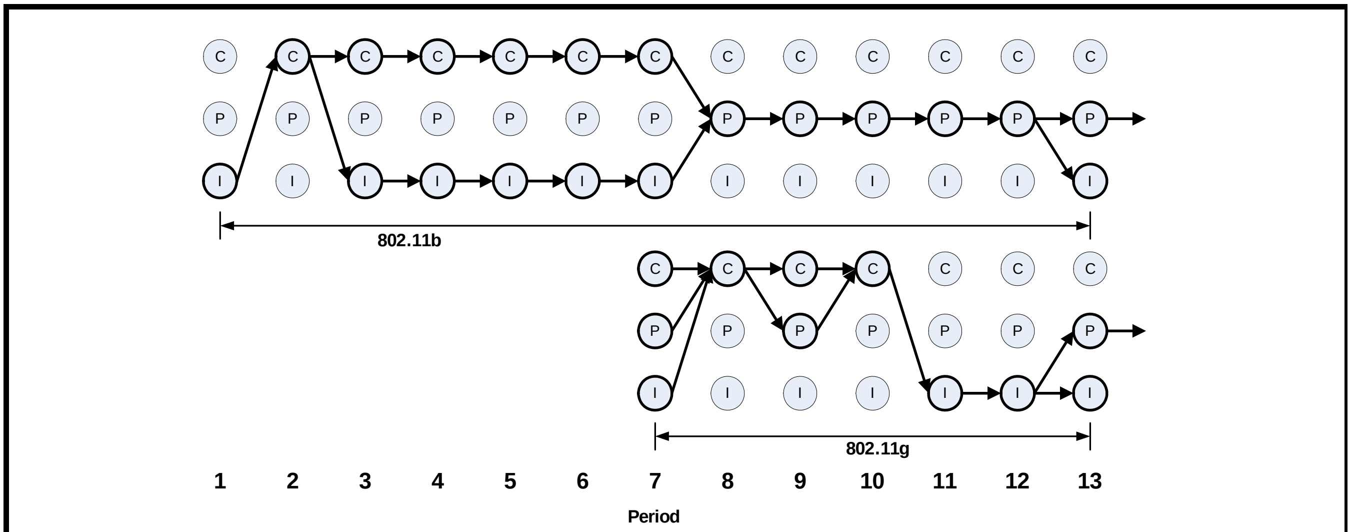

Figure 9. State Diagram for 802.11b and 802.11g Generations (6-month periods, starting March 2000)

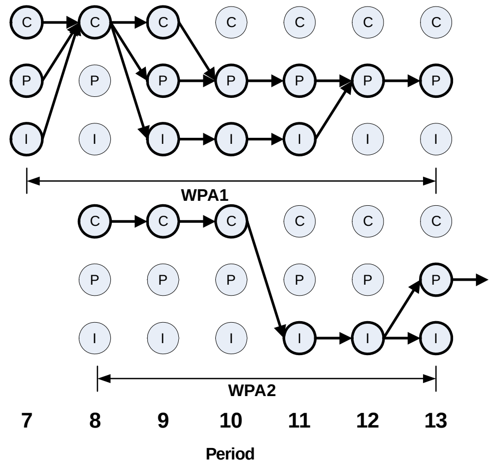

Figure 10. State Diagram for the WPA 1 and WPA 2 Generations (6-month periods, starting March 2000)

(Corner 2006). As of mid-2007, there had not yet been widespread adoption of 802.11n-ready infrastructure capabilities and clients, and sentiments in the marketplace have suggested some lag in next-generation wireless product technologies, as infrastructure capabilities catch up and consumers become aware of the benefits (Thornycroft 2007). As could be predicted from the state diagram analysis, in early to mid-2008, most PC manufacturers started shipping wireless chip sets that incorporated 802.11b, g, and n standards.

Comparison of Digital Music and Wireless Networking Technologies

The qualitative example of digital music evolution and the quantitative analysis of the wireless network technologies demonstrated that different patterns of technological change can occur in different ecosystems. The difference in the digital music and Wi-Fi evolutionary patterns might be explained in part by the influence of infrastructure technologies as either *supporting* or *enabling* other technologies within the ecosystem. Specifically, in the digital music ecosystem, infrastructure technologies typically play a supporting role—they are not required for the use of digital music products but provide additional value (e.g., online digital music stores, FM transmitters, P2P networks). In contrast, in the Wi-Fi ecosystem, infrastructure technologies had to be developed first simply to make wireless networking possible for product technologies. Then, as the ecosystem developed, new infrastructure technologies, such as wireless printers, supported the product technologies by providing additional value. The existence of two different types of infrastructure roles—supporting and enabling—provides a possible explanation of different evolutionary cycles across different ecosystems.

There are also other possible explanations for the different patterns in these ecosystems. For example, the types of consumers that purchase digital music technology products versus wireless networking technology products could be fundamentally different. The social construction of technology view (Bjiker et al. 1987) would argue that different social and cultural environments around the use of each technology lead to different patterns of innovation. Similarly, demand-driven theories of innovation (e.g., Adner and Levinthal 2001) would argue that the consumer and market will demand different functionality from the technologies in each of these ecosystems, and therefore their evolution should be different. As mentioned earlier, we plan to explore this issue in more detail in our future work.

Utility Evaluation of the Proposed Artifacts

To demonstrate the utility of our proposed artifacts, we follow Hevner et al. (2004), who suggested seven evaluation methods, two of which are appropriate for the context we have studied. The first of these is the *observational approach*, which is exemplified by *case study* and *interviewing* methods. In the previous two sections, we used two case studies to establish face validity of our proposed artifacts and demonstrate their application using both quantitative and qualitative approaches. In this section we report the results of a number of 1-hour semi-structured interviews with IT industry experts who assessed the use of the proposed artifacts by practitioners for analysis of the IT landscape. We also use the *descriptive approach* of artifact evaluation by employing the *informed argument method* using information from the knowledge base of our research domain to build arguments for the utility of our proposed artifacts. We accomplished this by assessing common techniques that are used in practice for technology forecasting, and discussing how our artifacts complement these techniques to improve IT landscape analysis capabilities.

Our proposed artifacts provide a novel approach to IT landscape analysis. This approach is not directly comparable to existing technology forecasting techniques on any specific quantitative performance measures because of its fundamentally different focus on technological change within an IT *ecosystem* (as opposed to other forecasting techniques that typically focus on evolution of either individual technologies or entire industry sectors). Therefore, we must rely on qualitative evaluation techniques. In an ideal evaluation scenario, a prediction of IT evolution would be made using the proposed techniques followed by a wait and then an assessment of the accuracy of the prediction. Since the ideal evaluation scenario is not possible in this context, combining case studies with interviews and comparative analysis provides the next best evaluation approach.

Interviews with IT Industry Experts

Conducting interviews is a key technique for performing IS case study research (Benbasat et al. 1987; Eisenhardt 1989) and is one of the most important data gathering tools in qualitative research (Myers and Newman 2007). Interviews provide a means for capturing extremely rich data and, in this case, can be used to evaluate the potential utility of our proposed artifacts in a business setting by allowing the informed opinions of IT industry experts to be captured.

The Interview Process

Our interview approach was based on an interview script that was pretested to ensure questions would be understood and properly interpreted, would yield the appropriate kinds of insights, and would be scoped to encourage open-ended input and help us to gauge the utility of the technological artifacts in our research. The interviewer ensured that all questions in the script were covered during the interview; however, related topics of discussion were permitted in order to increase the richness of the information captured. The interview included an opening for capturing basic background information, an introduction to explain the purpose of the interview, key questions, and a closing to provide a debriefing (Myers and Newman 2007). The interview questions are provided in the appendix.

Each interview participant was asked questions about (1) the business and organizational problem of analyzing the IT landscape for technology investment and development decision-making; (2) the utility of our proposed artifacts, based on their strengths and weaknesses in a context of use; and (3) potential improvements that might be appropriate to our proposed artifacts. Between the first two sets of questions, the participant was given a three-page handout that summarized our proposed approach for the first time. The interviewer subsequently spent, on average, 25 minutes explaining and demonstrating the proposed approach and answering clarification questions, using the handout as a guide. The interviews took, on average, one hour each.

Interview Subjects

We interviewed a set of IT industry experts with participants from four distinct populations: (1) IT industry senior executives, (2) IT industry consultants, (3) IT industry research staff and analysts, and (4) senior academic researchers with expertise on the IT industry. We chose these groups to represent the comprehensive set of perspectives of experts typically involved in the problem of IT landscape analysis. Using local industry and national academic contacts, we invited up to eight people in each group to participate in the interview process and selected a subset of participants to have a balanced sample based on availability and given time constraints. We interviewed a total of 12 experts, 3 in each group. All participants, with one exception, had over 10 years of IT industry experience, and over 10 years of experience in a management or senior decision-making role. All but one participant evaluated themselves as having a high level of understanding of the landscape of current and past information technologies (the exception self-reported a medium level of understanding). The participants hailed from Fortune 500 companies, technology research and government organizations, and well-known research universities. A summary description of the interview participants appears in Table 4.

Question Coverage

We asked questions to evoke the participants' opinions about four key aspects of using our artifacts for analyzing the IT landscape. (See Table 5.) First, we evaluated the *usefulness of the proposed constructs* in the ecosystem model. In particular, we asked whether the component, product, and infra-

Table 4. Descriptive Summary of Interview Participants	
Characteristic	**Description**
Years IT of Experience	All but one participant had more than 10 years work experience in IT or IT related fields. The one exception had greater than 5 years of experience.
Self-Reported Expertise on IT Landscape	All but one of the participants self-rated as having "high" level of expertise on the IT landscape (out of three choices: low, medium, high). The one exception selected "medium."
Participant Professions Represented	Senior IT executives (3), senior IT consultants (3), senior IT analysts or industry researchers (3), senior IT-related academic researchers (3).
Industries Represented	IT services and consulting, IT hardware manufacturing, software, medical device manufacturing, materials/general manufacturing, retail, transportation, government IT office, government research lab, university research lab, university business school.

Table 5. Coverage of Interview Questions: Key Issues for Evaluation	
Issue	**Description**
Constructs	Is the ecosystem model, with its technology roles and paths of influence, a useful approach for representing the evolution of ITs? Does this representation improve managerial capabilities for analysis? Does it aid the processes of IT investment and development decision-making?
Logic of Methodology	Are the qualitative and quantitative methodologies we propose for identifying trends in technology evolution sound? Do they produce new insights?
Information Produced	Is the information produced by the proposed artifacts useful to practitioners? Does it aid in IT investment and development decision-making?
Relationship to Existing Techniques	Do the proposed artifacts complement existing techniques to provide new insights and improved analysis of IT evolution?

structure roles provided a useful model for representing technologies within an ecosystem. We also queried their opinions about the use of paths of influence to classify temporal relationships. Second, we evaluated the *logic of the qualitative and quantitative methodologies* for identifying and visualizing trends in the IT landscape. Here our questions directed the discussion to the soundness of the methodologies and the insights produced by following them. Third, we evaluated the *utility of the information produced* by the proposed qualitative and quantitative methodologies. Here we directed the discussion to the participants' opinions about the usefulness of the information about technology trends to practitioners and organizations involved in the IT investment or development decision-making process. We also captured opinions about the format and understandability of the output graphs and diagrams. Fourth, we captured their opinions about *how our methods complement existing approaches* for analyzing the IT landscape. The participants' feedback regarding these four issues led us to identify several key dimensions of utility for our proposed artifacts.

Results of the Interviews: Key Dimensions of Utility

Responses to the first set of interview questions provided motivation and shaping of the business and organizational problem our proposed artifacts address. Several key insights came out of this part of the interview. On average, the participants indicated the importance of historical, current, and future IT landscape analysis to IT investment decision making as 3.7, 4.6, and 4.5 (on a scale 1 to 5), respectively. (Table 6 provides summary statistics of numeric questions we asked in the interview.) The majority of participants (9 of 12) independently noted that the staff and management of most IT-consuming companies do not have the time or expertise to perform the necessary analysis of the IT landscape, and so they must outsource this process to third parties. Additionally, every participant independently noted the reliance of IT organizations on reports produced by the companies like Gartner, Forrester, and IDC. Multiple participants (6 of 12) also noted that current IT investments and partnerships play

Table 6. Interview Findings: Summary Statistics of Numerical Questions

Question	Mean	Std. Dev.
Importance of historical technology analysis in IT investment decision making. (1 = very unimportant, 5 = very important)	3.7	1.15
Importance of evaluating current IT landscape for IT investment decision making. (1 = very unimportant, 5 = very important)	4.6	0.67
Importance of predicting future IT landscape for IT investment decision making. (1 = very unimportant, 5 = very important)	4.5	0.67
Effectiveness of existing methods and techniques for analyzing IT landscape. (1 = very ineffective, 5 = very effective)	2.9	0.52
Effectiveness of the proposed methodology for analyzing IT landscape. (1 = very ineffective, 5 = very effective)	4.2	0.39

Note: N = 12 for all questions.

a significant role in future investments, and often IT investment decisions are outsourced to partners and suppliers. These insights reinforced the importance of providing new techniques to aid practitioners in evaluating trends in the IT landscape.

In general, all of the participants found value in our proposed artifacts for evaluating the IT landscape and providing aid in predicting future technology trends, rating the potential effectiveness of using our proposed artifacts as 4.2 (on a scale 1 to 5), as shown in Table 6. Four key dimensions about the utility of our proposed artifacts consistently emerged in their opinions regarding the value of our research. These dimensions were identified from the interpretation of points independently made by several interview participants. In particular, we found that the proposed artifacts support complexity reduction, help to structure investment decisions, provide a formal method for quantifying technology ecosystem evolution, and support the identification of the locus of value for post-investment evaluation. We discuss each of these in succession, and provide our respondents' reactions to illustrate our arguments about utility. Table 7 provides a summary of our interview findings with respect to the different dimensions of utility.

Complexity Reduction

The general consensus of the experts we interviewed was that the use of technology roles and the paths of influence provide a novel and useful way of reducing the complexity of the IT landscape while maintaining the important relationships among technologies. Ten of the twelve respondents independently made comments to this effect; for example:

> *[The roles and model] are very clever because you compress the universe of possibilities and make the ecosystem understandable.* – Senior Technology Analyst at a Fortune 500 transportation company

> *This is a very good way to think about the problem ... it explains the technology ecosystem very well and is nice way of trying to break up very complex phenomena.* – Managing Director of a Government IT Organization

The exercise of defining the technology ecosystem provides two useful insights to the user of the proposed constructs from the points of view of our respondents. First, it forces the analyst to consider *interdependencies* among technologies and realize the *complexity* of the technology ecosystem. Second, it provides structure (based on the concepts of technology roles and paths of influence) to reduce this complexity using a system view of the IT landscape and captures the technology ecosystem from the analyst's point of view. Each of these aspects enhances the user's ability to understand the nature of relationships in the IT landscape.

Structure for IT Investment Decision-Making

The interviewees also reported:

> *This approach provides structure to the conversation and decision-making process for IT investment.* – Director of Business Development at a major university IT-related research center

> *This [approach] brings the ability to work on [the IT investment decision-making problem] interdisciplinarily [sic] within an organization. You could present this to the CEO, engineering guys, marketing guys, and they would all know what you were talking about. They may ask different questions, but*

Table 7. Interview Findings: Dimensions of Utility

Dimension	Description	Representative Quote	Count
Complexity Reduction	Technology roles and paths of influence provide a novel and useful way of reducing IT landscape complexity.	"*[The roles and model] are very clever because you compress the universe of possibilities and make the ecosystem understandable.*" – Senior technology analyst at a Fortune 500 transportation company	10
Structuring IT Investment Decision Making	The IT ecosystem methodology provides a means for identifying IT trends that are relevant to a specific firm's interests and business contexts.	"*This approach provides structure to the conversation and decision-making process for IT investment.*" – Director of business development at a major university IT related research center	10
Formal Method	The IT ecosystem model and methodology provide a much needed formal technique for quantifying complex trends in the IT landscape.	"*The systematic approach this [methodology] provides is useful….Most strategic IT decisions are made using less formal types of analysis.*" – Senior technology analyst at a Fortune 500 transportation company	7
Multiple Loci of Value	The IT ecosystem model provides value to both decision makers that use the information produced by using the methodology and analysts that employ the methodology in their technology forecasts.	"*For analysis purposes, this sort of model is very good and should definitely help analysts at Gartner or Forrester produce reports for managers.*" – IT manager at a Fortune 500 retail company	7
Methodological Complementarities	The IT ecosystem model and methodology complement well existing techniques for forecasting technological development.	"*This [approach] should be very useful for helping educate analysts about the [IT] landscape. It is complementary to other existing approaches*." –Senior researcher at a Fortune 500 technology company	10

Note: "Count" column refers to the number of interview participants (out of 12) that independently made comments that agreed with the corresponding utility dimension.

> *they would all find it useful.* – Former VP of a Fortune 500 technology company, current IT industry private consultant

Through the interviews we discovered evidence of a lack of structure in how firms go about analyzing the IT landscape. They typically rely on third-party reports and advice from suppliers and partners, as we noted earlier, but this apparently is still not sufficient. Ten of the twelve respondents noted that our proposed methodology provides a means for generating representations of the IT landscape and associated technology trends that are relevant to the firm's interests and business contexts. Six of the twelve participants also noted that the proposed approach is a useful tool for decision-makers across different functional roles in the organization. The participants felt that senior managers and strategic planners, as well as technical managers and engineers, could all benefit from understanding the IT landscape and technology trends in terms of the proposed technology ecosystem model. In general, the consensus of the participants was that the proposed methods should be useful in the IT investment and development decision-making process.

Formal Method to Quantify Technological Change

Seven of the twelve respondents made comments that the proposed methods provide a much-needed formal technique for quantifying trends in technological change within the IT landscape. Our interviewees noted that the techniques most commonly used by firms to analyze the IT landscape are informal and *ad hoc.*

> *Most work on this problem is informal and this is one of only a few formal approaches I have seen. Attempts to formally quantify things are a good thing. This is a formal methodology to add some quantification to the analysis by [companies like Gartner].* – Senior Consultant at a Fortune 500 technology company

> *The systematic approach this provides is useful.… Most strategic IT decisions are made using less formal types of analysis.* – Senior Technology Analyst at a Fortune 500 transportation company

We gathered from our interviews that only a few firms—including those producing industry reports—use formal quantitative means to produce technology forecasts, aside from simple linear extrapolation. All participants found the quantification aspect of the proposed methods to be useful, and 9 out of 12 also commented that our formal approach will complement existing techniques well and will provide firms with new and useful information for making IT investment and development decisions.

Locus of Value for the Artifacts

We also learned where the value of our proposed artifacts will be the highest, which is another important aspect of their utility. This is similar to the *locus of value* construct (Kauffman and Weill 1989), which describes where value flows are most likely to occur. A consultant and a senior manager offered the following comments:

> *Companies that can benefit most from this are the technology producers, like for example IBM, Microsoft, and Sun. These are the ones defining the future technologies. By looking at a systematic way of how technology got to where it is today it may help [technology producers] determine what types of technologies are needed.* – Senior Consultant at a Fortune 500 technology company

> *For analysis purposes, this sort of model is very good and should definitely help analysts at Gartner or Forrester produce reports for managers.* – IT Manager at a Fortune 500 retail company

Based on interviews, an interesting finding for us was that, in terms of the locus of value, the interview participants differentiated between the utilities of different artifacts: (1) the utility of the proposed model, constructs, and the information produced by our methods (i.e., resulting graphs and diagrams of specific ecosystems), and (2) the utility of methodologies themselves for conducting IT landscape analysis and producing various patterns of technology evolution. The participants indicated that the *information produced by our proposed methods* would be useful to decision makers in both IT-consuming and IT-producing firms. On the other hand, the majority of the interview participants (7 of 12) felt that *using the proposed approach to actually conduct the analysis of the IT landscape* would be most beneficial to firms that either produce IT or produce the industry reports on trends in IT. Understanding the trends in technology evolution that led to the current state of the IT landscape should prove vital in determining what directions IT development initiatives should follow in the future. Furthermore, the reality of IT landscape analysis is that IS and corporate strategy staff members at most IT-consuming firms do not have the time, the resources, or the technology and market knowledge to conduct formal analyses. So, even if the techniques for analyzing the landscape improve, IT-consuming firms will still likely rely on third parties to conduct their technology assessments and analyses for them. As a result, new formal approaches for analyzing the IT landscape, such as what we propose, should add value to both the firms producing the forecasts and the firms consuming them. Our findings with respect to locus of value also suggest that, for firms that continue to outsource their IT landscape analysis and decision-making tasks, these outsourcing decisions can be more informed. The proposed methodologies could be used to help IT-consuming firms better understand the IT investment decision-making process with the help of third parties (e.g., consultants and vendors).

The Fifth Dimension: The Complementary Value of the Proposed Artifacts

> *This [approach] should be very useful for helping educate analysts about the [IT] landscape. It is complementary to other existing approaches.* – Senior Researcher at a Fortune 500 technology company

An additional aspect of utility suggested by most of the interview participants (10 of 12) was that our proposed methods will complement well existing techniques for analyzing the IT landscape. To delve deeper into the potential complementarities, we evaluated the strengths and weaknesses of many common approaches for technology forecasting and IT landscape analysis and discuss how our approach specifically complements each of them.

Table 8 provides an outline of common technology forecasting and planning techniques used in industry, including trend analysis, expert opinion, modeling and simulation, and scenario analysis. Although specific methods are most often proprietary, firms, such as Gartner, Forrester, and IDC, use some version and/or combination of these techniques to generate their IT forecasts and reports. These reports typically are narrative summaries of entire industry sectors based on market and financial information as well as expert opinions that are obtained in a sequential Delphi-type approach. These reports often focus on trajectories of diffusion, cost forecasts, and impact of current technologies. In contrast, our approach

Table 8. Overview of the Traditional Technology Forecasting/Modeling Methods and How Our Approach Complements Them

	Trend Analysis	Expert Opinion	Modeling and Simulation	Scenarios
Description	Historical trends are extended into the future using mathematical and statistical techniques.	Domain expert opinions are collected and analyzed.	Simplified representation of structure and dynamics of real world created to forecast or simulate future outcomes.	Plausible set of outcomes for some aspect of future is created and analyzed.
Examples	Extrapolation, time series estimation, regression and econometrics, S-curve estimation	Delphi method, interviews, questionnaires, idea generation	Cross-impact analysis, system dynamics analysis, path and tree analysis	Descriptive vs. normative scenarios, baseline vs. optimistic vs. pessimistic scenarios
Assumptions	Past trends will continue into future.	Experts know significantly more about a domain than others. Group opinions are better than individual opinions.	Complex structures and processes can be captured effectively by simplified models.	Imaginative descriptions can reasonably capture the full set of future possibilities.
Strengths	Quantifiable and data-based forecasts, short-term accuracy	Experts typically possess detailed knowledge of subject matter that produces high-quality forecasts.	Models reduce complexity and highlight the most important factors. Process of building a model can provide insights.	Effective way to communicate forecasts. Incorporate a wide range of qualitative and quantitative data.
Weaknesses	Requires a significant amount of data, which can be difficult to obtain. Can be inaccurate for long time horizons.	Difficult to identify experts. Knowledge is typically implicit (internalized). Group forecasts may be affected by social and psychological factors.	Models often ignore qualitative and contextual factors.	Can be highly speculative and not firmly based in reality.
Our Approach Complements This by Method Providing:	A view of relationships between multiple technologies that complements and informs in-depth analysis of a single technology attribute.	A formal quantitative approach and a representation of the past and current IT landscape that can structure discussion among experts.	A representation of the structure of the IT landscape that can inform the development of a more realistic simulation.	A formal representation of the past and present ecosystem which can be used as quantifiable input for generating scenarios.

Note: Based on the technology forecasting methods discussed in Millet and Honton (1991) and Porter et al. (1991).

utilizes elements of trend analysis and modeling techniques, enables mapping of the historical relationships among specific technologies, and can provide useful insights regarding the next possible evolutionary steps within a specific ecosystem. In particular, our approach may complement existing technology forecasting methods (as noted in the last row of Table 8) by providing structured input and formal analysis of the past and current states of the IT landscape.

Another relevant industry analysis approach is a technology roadmap. A *technology roadmap* is a tool that is typically used for planning purposes, such as in product, strategic, service/capability, and process planning (Kostoff and Schaller 2001; Phaal et al. 2004; Rinne 2004). Technology roadmaps provide a way to identify, evaluate, and select strategic alternatives by mapping structural and temporal relationships among research and development, technologies, potential products, and markets. The process of generating a technology roadmap follows a visual mapping strategy not unlike the one we have presented. Our methods complement technology roadmaps by providing a problem representation vocabulary that extends current road-mapping techniques, and provides a more formal quantitative method for identifying trends in technological change. Technology roadmaps are designed to outline the set of possible future strategies for a specific firm, and our technique adds to this by providing a method for historically evaluating the evolution of an entire set of interrelated technologies (represented by technology roles within the ecosystem) using similar visual representation techniques.

As noted in Table 8, all technology forecasting methods have inherent assumptions, and the accuracy of these assumptions influences the predictive accuracy of the forecast. Most of these methods, with the exception of some regression and econometric approaches, are not predictive in the sense of classical variance theory (Mohr 1982), where a set of predictor variables is used to predict the level of some outcome variable. The basic assumption in all forecasting techniques, including the ones that a variance theory would suggest, is that the historical trends and patterns will continue into the future following the same dynamics. Our approach follows the same basic assumption: If technological change will continue to occur following the same patterns identified using our methods, then we can make reasonable forecasts about the future.

Conclusions, Limitations, and Future Work

Following the design science research paradigm, the major contribution of this research is the development of a new set of artifacts designed to help IT practitioners and researchers make sense of the IT landscape and identify, analyze, and predict technological trends. Specifically, the artifacts provide tools for (1) codifying technological innovations based on the role they play within an ecosystem of interrelated technologies, (2) identifying dominant technology roles within an ecosystem using real-world data, and (3) visually representing patterns of technological change over time based on dominant technological roles. We build on prior management research that uses the ecosystem analogy by operationalizing constructs for analyzing relationships between technologies within the IT landscape. We evaluated the proposed artifacts in several ways. First, we used a qualitative case study of digital music technologies and a quantitative case study of wireless networking technologies to demonstrate the face validity of the proposed artifacts and their applicability to real-world business problems. Second, we conducted in-depth interviews with several IT industry experts to assess the use of the proposed artifacts by practitioners for analyzing the IT landscape. Finally, we provided a comparison of the proposed artifacts to existing technology forecasting techniques to highlight complementarities.

This work contributes to the IS research field in several additional ways. We provide a review of relevant IS and organizational science research on technology evolution and construct a theoretical perspective that integrates and builds upon previous ideas. We demonstrate strategies for sense-making of complex data (e.g., quantification and visual mapping) from process theory. In addition, we provide insightful analysis on the evolution in two contemporary and important IT ecosystems: digital music and wireless networking technologies. We also review and compare existing technology forecasting methods.

The visual mapping and quantitative strategies for sense-making from process data that we used to develop our proposed artifacts do have their limitations. Process mapping and visual representations may exclude some dimensions of data ambiguity, and graphical forms may be biased toward the representation of certain types of information over others. The conclusions derived may sometimes have rather mechanical qualities since these representations deal more with the surface structure of activity sequences than the underlying forces. On the other hand, since the goal of quantification strategies is to reduce complexity, their use may sometimes lead to a loss of richness in the process data (Langley 1999). To address the limitations of process theory, Langley (1999) and Van de Ven (1992) suggest that both the quantitative and visual mapping strategies should be used in combination with other approaches, as we have done in this work by using the two together. Visual mapping provides additional contextual information that may be lost in quantification, while quantification provides an opportunity to apply empirical rigor that is missing in visualization.

All models are abstractions of the real world and, therefore, depend on the assumptions used in their construction. In this research we relied on the assumption, based on our synthesis of prior literature and our observations of the real world, that the common roles technologies play in an ecosystem are components, products, and infrastructure. Another choice we make in this model is to currently exclude the role of external forces, such as market dynamics, the demand environment, society, and culture. Although an objective of our approach is to demonstrate that the patterns of technological change can be identified using a model based solely on relationships between technologies, multiple interview participants recommended expanding our model in future research to include external forces and context-specific factors. Excluding these factors may result in a loss of contextual richness; however, by limiting the number of factors considered in the model, we gain control and specificity and reduce complexity for the user of our methods. Additionally, we found in our example analyses that supporting and enabling infrastructure technologies can result in different patterns of technology evolution. This provides a starting point for future work on developing new theories about the role of infrastructure in technology evolution.

The interview participants who evaluated our proposed artifacts provided three additional important recommendations and comments for expansions to the current research. First, there was a suggestion that exploring the directionality of paths of influence may provide interesting insights on technological development. In the current model, we looked primarily at positive relationships—an innovation of a technology in one role provides an opportunity for the development of a new technology in another role. The negative relationships between technologies may also provide important insights. For example, a new technology may make a series of existing technologies obsolete, thus effectively exterminating a portion of the ecosystem. Considering the directionality of the relationships between technologies also reinforces the ecological analogy in which both birth and death processes occur. Second, the time scale may be used more effectively in quantitative analysis to identify lags in transitions between patterns in technology trends. Quantifying such lags may provide a predictive tool for forecasting the occurrence of future trends. Third, two of the interview participants noted that they would expect data collection for performing the proposed analysis to be difficult for many firms. We recognize the importance of this comment and note that many technology services companies are investing significantly in new business intelligence tools for extracting quantifiable data from the seas of information available on and off the Internet. As these tools evolve, rich data on the IT landscape should become more readily available, and we plan to investigate opportunities for integrating our proposed approach with these tools.

Modeling the IT landscape is a difficult, complex, and important problem and there are many potential extensions to the current work. The notion of path dependence (i.e., that a dynamic process is governed by its own history) aligns well with our proposed methodology and provides interesting avenues for extensions to our research. As noted by David (2007, p. 1), path dependence figures especially prominently in "the analytical consciousness of all who are concerned to study the evolution of technologies." The idea of path dependence emphasizes a broader and more influential role of history, which is in contrast to many traditional approaches of economic and social science analyses that focus on finding stable, unique equilibrium of a system. Path dependence also emphasizes the effect of initial conditions and historic events, which can have an influential impact on future outcomes. Additionally, the role of agents, such as engineers and policy makers, and the decisions that they make based on current system conditions can have a substantial impact on the future system dynamics. Applying the formal definitions and modeling techniques of path dependence in stochastic processes and dynamic systems to the IT ecosystem model is a promising extension to our research that we plan to explore.

Simulation provides an advantageous approach for modeling the system dynamics of an IT ecosystem and would allow us to extend the current research and include the role of agents, external forces (e.g., demand and social environment), and the formalisms of path dependence. In addition, the current lack of structured data and the general complexity of the IT landscape provide further reasons for exploring simulation techniques. Simulation can be used to explore the emergent behavior of IT ecosystems and incorporate additional structures into the system, such as firms and consumers.

Finally, to continue to provide useful tools to practitioners and researchers who are analyzing the IT landscape, we plan to explore combining design science with action research to extend this work with research methods that have a more proactive orientation (Cole et al. 2005). Action research is an iterative problem-solving process that involves researcher and practitioner acting together to conduct relevant IS research (Avison et al. 1999). Combining the action and design science research approaches will inform the refinement and extension of our IT ecosystem model and improve the utility of the resulting artifacts for analyzing the IT landscape.

Acknowledgments

The authors would like to thank the Digital Technology Center and the Carlson School of Management, University of Minnesota, for providing joint financial support of this research. Rob Kauffman thanks the MIS Research Center, the Center for Advancing Business through Information Technologies, and the W. P. Carey Chair for partial support. The authors would also like to thank the organizers and participants of the "Innovation and Innovation Management" mini-track at the 2006 Hawaii International Conference on System Sciences for valuable comments and discussion on related prior work. We also thank the IT experts who willingly provided their valuable time for evaluating constructs and methods developed in this research. The special issue guest editors, Sal March and Veda Storey, were instrumental in helping us to develop this research. We also are indebted to the anonymous associate editor and three reviewers, who offered useful assistance and guidance for improving the quality of our manuscript. We would also like to thank Donna Sarppo from the MIS Research Center, University of Minnesota, for her help in coordinating interviews.

References

Abbott, A. 1990. "A Primer on Sequence Methods," *Organization Science* (1:4), November, pp. 375-392.

Adner, R., and Levinthal, D. 2001. "Demand Heterogeneity and Technology Evolution: Implications for Product and Process Innovation," *Management Science* (47:5), May, pp. 611-628.

Adomavicius, G., Bockstedt, J., Gupta, A., and Kauffman, R. J. 2007. "Technology Roles and Paths of Influence in an Ecosystem Model of Technology Evolution," *Information Technology and Management* (8:2), April, pp. 185-202.

Arthur, W. B. 1989. "Competing Technologies, Increasing Returns, and Lock-In by Historical Events," *Economic Journal* (99:394), March, pp. 116-131.

Avison, P., Lau, F., Myers, M., and Nelson, P. A. 1999. "Action Research," *Communications of the ACM* (42:1), January, pp. 94-97.

Bacon, C. J. 1992. "The Use of Decision Criteria in Selecting Information Systems/Technology Investments," *MIS Quarterly* (16:3), September, pp. 335-353.

Baldwin, C. Y., and Clark, K. B. 1997. "Managing in the Age of Modularity," *Harvard Business Review* (75:5), September, pp. 84-93.

Baldwin, C. Y., and Clark, K. B. 2000. *Design Rules: The Power of Modularity*, Cambridge, MA: MIT Press.

Benbasat, I., Goldstein, D. K., and Mead, M. 1987. "The Case Research Strategy in Studies of Information Systems," *MIS Quarterly* (11:3), September, pp. 369-386.

Benbasat. I., and Zmud, R. W. 2003. "The Identity Crisis Within the Is Discipline: Defining and Communicating the Discipline's Core Properties," *MIS Quarterly* (27:2), June, pp. 183-194.

Bjiker, W., Hughes, T., and Pinch, T. 1987. *The Social Construction of Technological Systems*, Cambridge, MA: The MIT Press.

Boland, R. J., Lyytinen, K., and Yoo, Y. 2003. "Path Creation with Digital 3D Representation: Networks of Innovation in Architectural Design and Construction," *Sprouts: Working Papers on Information Environments, Systems and Organizations* (3:1), Winter, pp 1-28.

Campbell, D. T. 1990. "Levels of Organization, Downward Causation, and the Selection-Theory Approach to Evolutionary Epistemology," in *Theories of the Evolution of Knowing*, G. Greenberg and E. Tobach (eds.), Hillsdale, NJ: Lawrence Erlbaum, pp. 1-17.

Clark, K. B. 1985. "The Interaction of Design Hierarchies and Market Concepts in Technological Evolution," *Research Policy* (14:5), October, pp. 235-251.

Clemons, E. K and Weber, W. 1990. "Strategic Information Technology Investments: Guidelines for Decision Makers," *Journal of Management Information Systems* (7:2), Fall, pp. 9-28

Cole, R., Purao, S., Rossi, M., and Sein, M. K. 2005. "Being Proactive: Where Action Research Meets Design Research," in *Proceedings of the 26th International Conference on Information Systems*, D. E. Avison, D. F. Galletta, and J. I. DeGross (eds.), Las Vegas, NV, December 11-14, pp. 325-336.

Corner, S. 2006. "Dell Puts Next Gen WiFi, 802.11n, into Laptops," *ITWire*, July 18 (available at www.itwire.com.au/content/view/4995/127/; accessed January 10, 2008).

David, P. 2007. "Path Dependence—A Foundational Concept for Historical Social Science," *Cliometrica – Journal of Historical Economics and Econometric History* (1:2), Summer, pp. 91-114.

Dosi, G. 1982. "Technological Paradigms and Technological Trajectories," *Research Policy* (11:3), June, pp. 147-162.

The Economist. 2007. "Old Parts, but New Whole," November 8, (available at www.economist.com/specialreports/displaystory.cfm?story_id=10053214; accessed January 10, 2008).

Eisenhardt, K. M. 1989. "Building Theories from Case Study Research," *Academy of Management Review* (14:4), October, pp. 532-550.

Ewing, J., and Burrows, P. 2006. "Will Apple Answer Sony's Call?," *Business Week*, July 31 (available at www. businessweek.com/magazine/content/06_31/c3995016.htm; accessed January 10, 2008).

Funk, J. L. 2007. "Technological Change Within Hierarchies: The Case of the Music Industry," *Economics of Innovation and New Technology* (16:1), January, pp. 1-16.

Garcia, A. 2006. "First 802.11n Products Show Standard's Promise," *eWeek*, April 24 (available at www.eweek.com/article2/0,1895,1952659,00.asp; accessed January 10, 2008).

Garud, R., and Van de Ven, A. H. 1992. "An Empirical Evaluation of the Internal Corporate Venturing Process," *Strategic Management Journal* (13:Special Issue), Summer, pp. 93-109.

Gregor, S. 2006. "The Nature of Theory in Information Systems," *MIS Quarterly* (30:3), September, pp. 611-642.

Hannan, M. T., and Freeman, J. 1977. "The Population Ecology of Organizations," *American Journal of Sociology* (82), March, pp. 929-964.

Hannan, M. T., and Freeman, J. 1989. *Organizational Ecology*, Cambridge, MA: Harvard University Press.

Harte, J., Shireman, B., Burke, A., and Scarlett, L. 2001. "Business as a Living System: the Value of Industrial Ecology (A Roundtable Discussion)," *California Management Review* (43:3), Spring, pp. 16-25.

Hevner, A. R., March, S. T., Park, J., and Ram, S. 2004. "Design Science in Information Systems Research," *MIS Quarterly* (28:1), March, pp. 75-105.

Iansiti, M., and Levien, R. 2002. "The New Operational Dynamics of Business Ecosystems: Implications for Policy, Operations and Technology Strategy," Working Paper 03-030, Harvard Business School, Cambridge, MA.

Iansiti, M., and Levien, R. 2004. *The Keystone Advantage: What New Dynamics of Business Ecosystems Mean for Strategy, Innovation, and Sustainability*, Boston: Harvard Business School Press.

Kauffman, R. J., and Weill, P. 1989. "An Evaluative Framework for Research on the Performance Effects of Information Technology Investment," in *Proceedings of the 10th International Conference on Information Systems*, J. I. DeGross, J. C. Henderson, and B. R. Konsynski (eds.), Boston, MA, December 4-6, pp. 377-388

Kostoff, R. N., and Schaller, R. R. 2001. "Science and Technology Roadmaps," *IEEE Transactions on Engineering Management* (48:2), May, pp. 132-143.

Langley, A. 1999. "Strategies of Theorizing from Process Data," *Academy of Management Review* (24:4), October, pp. 691-710

Langley, A., and Truax, J. 1994. "A Process Study of New Technology Adoption in Smaller Manufacturing Firms," *Journal of Management Studies* (31:5), September, pp. 619-652.

Laudan, R. (ed.). 1984. *Nature of Technological Knowledge: Are Models of Scientific Change Relevant?*, Dordrecht, Netherlands: Reidel.

Lyytinen, K., and Rose, G. M. 2003. "The Disruptive Nature of Information Technology Innovations: The Case of Internet Computing in Systems Development Organizations," *MIS Quarterly* (27:4), December, pp. 557-595.

Malerba, F., Nelson, R., Orsenigo, L., and Winter, S. 1999. "History-Friendly Models of Industry Evolution: The Case of Computer Industries," *Industrial and Corporate Change* (8:1), March, pp. 1-36.

March, S. T., and Smith, G. F. 1995. "Design and Natural Science Research on Information Technology," *Decision Support Systems* (15:4), December, pp. 251-266.

Markus, L., and Robey, D. 1988. "Information Technology and Organizational Change: Causal Structure in Theory and Research," *Management Science* (34:5), May, pp. 583-598.

Meyer, A. D. 1991. "Visual Data in Organizational Research," *Organization Science* (2:2), May, pp. 218-236.

Meyer, A. D., and Goes, J. 1988. "Organizational Assimilation of Innovations: A Multilevel Contextual Analysis," *Academy of Management Journal* (31:4), December, pp. 897-923.

Miles, M. B., and Huberman, A. M. 1994. *Qualitative Data Analysis*, Newbury Park, CA: Sage Publications.

Millet, S. M., and Honton, E. J. 1991. *A Manager's Guide to Technology Forecasting and Strategy Analysis Methods*, Columbus, OH: Battelle Press.

Mintzberg, H., Raisinghani, D., and Theoret, A. 1976. "The Structure of Unstructured Decision Processes," *Administrative Science Quarterly* (21:2), June, pp. 246-275.

Mohr, L. B. 1982. *Explaining Organizational Behavior*, San Francisco: Jossey-Bass.

Myers, M. D., and Newman, M. 2007. "The Qualitative Interview in IS Research: Examining the Craft," *Information and Organization* (17:1), January, pp. 2-26.

Nelson, R. R. 1995. "Recent Evolutionary Theorizing about Economic Change," *Journal of Economic Literature* (33:1), March, pp. 48-90.

Nelson, R. R., and Winter, S. G. 1982. *An Evolutionary Theory of Economic Change*, Cambridge, MA: Belknap Press.

Newman, M., and Robey, D. 1992. "A Social Process Model of User-Analyst Relationships," *MIS Quarterly* (16:2), June, pp. 249-266.

Nickerson, J. V., and zur Muehlen, M. 2006. "The Ecology of Standards Processes: Insights from Internet Standard Making," *MIS Quarterly* (30:Special Issue), August, pp. 467-488.

Orlikowski, W. J. 1993. "CASE Tools as Organizational Change: Investigating Incremental and Radical Changes in Systems Development," *MIS Quarterly* (17:3), September, pp. 309-340.

Orlikowski, W. J., and Robey, D. 1991. "Information Technology and the Structuring of Organizations," *Information Systems Research* (2:2), June, pp. 143-169.

Pentland, B. T. 1995. "Grammatical Models of Organizational Processes," *Organization Science* (6:5), September, pp. 541-556.

Phaal, R., Farrukh, C. J. P., and Probert, D. R. 2004. "Technology Roadmapping – A Planning Framework for Evolution and Revolution," *Technological Forecasting and Social Change* (71:1), January, pp. 5-26.

Porter, A. L., Roper, A. T., Mason, T. W., Rossini, F. A., and Banks, J. 1991. *Forecasting and Management of Technology*, New York: Wiley-Interscience.

Quaadgras, A. 2005. "Who Joins the Platform? The Case of the Rfid Business Ecosystem," in *Proceedings of the 38th Hawaii International Conference on System Sciences*, R. H. Sprague (ed.), Big Island, HI, January 3-6, Los Alamitos, CA: IEEE Computing Society Press.

Rinne, M. 2004. "Technology Roadmaps: Infrastructure for Innovation," *Technological Forecasting and Social Change* (71:1), January, pp. 67-80.

Romanelli, E., and Tushman M. 1994. "Organizational Transformation as Punctuated Equilibrium," *Academy of Management Journal* (37:5), October, pp. 1141-1166.

Rosenkopf, L., and Nerkar, A. 1999. "On the Complexity of Technological Evolution: Exploring Coevolution Within and Across Hierarchical Levels in Optical Disk Technology," in *Variations in Organization Science: In Honor of Donald T. Campbell*, J. A. C Baum and B. McKelvey (eds.), Thousand Oaks, CA: Sage Publications, 1999, pp. 169-183.

Sahal, D. 1981. *Patterns of Technological Innovation*, Reading, MA: Addison-Wesley.

Sahal, D. 1985. "Technological Guideposts and Innovation Avenues," *Research Policy* (14:2), April, pp. 61-82.

Saviotti, P. P. 1996. *Technology Evolution, Variety and the Economy*, Cheltenham, UK: Edward Elgar Publishing.

Saviotti, P. P., and Metcalfe, J. S. 1984. "A Theoretical Approach to Construction of Technological Output Indicators," *Research Policy* (13:3), June, pp. 141-51.

Shillingford, J. 2005. "Sony Ericsson launches Walkmans," *BBC News*, February 14 (available at news.bbc.co.uk/1/hi/business/4265777.stm; accessed January 10, 2008).

Smith, M. R., and Marx, L. (eds.). 1994. *Does Technology Drive History? The Dilemma of Technological Determinism*, Cambridge, MA: MIT Press.

Sood, A., and Tellis, G. J. 2005. "Technological Evolution and Radical Innovation," *Journal of Marketing* (69:3), July, pp. 152-168.

Star, S. L., and Ruhleder, K. 1999. "Steps Toward and Ecology of Infrastructure: Design and Access for Large Information Spaces," *Information Systems Research* (7:1), March, pp. 111-134.

Thornycroft, P. 2007. "Designing for Speed: Preparing for the 802.11n Adoption Wave," *The Edge*, Aruba Networks, Sunnyvale, CA, August 6 (available at edge.arubanetworks.com/article/designed-speed-preparing-802-11n-adoption-wave; accessed January 10, 2008).

Van Buskirk, E. 2005. "Bragging Rights to the World's First MP3 Player," *CNET News*, January 25 (available at news.com.com/2010-1041_3-5548180.html; accessed January 10, 2008).

Van de Ven, A. H. 1992. "Suggestions for Studying Strategy Process: A Research Note," *Strategic Management Journal* (13:Special Issue), Summer, pp. 169-188.

Van de Ven, A. H., and Huber, G. P. 1990. "Longitudinal Field Research Methods for Studying Processes of Organizational Change," *Organization Science* (1:3), August, pp. 213-219.

Van de Ven, A. H., and Poole, M. S. 1990. "Methods for Studying Innovation Development in the Minnesota Innovation Research Program," *Organization Science* (1:3), August, pp. 313-335.

Weick, K. 1979. *The Social Psychology of Organizing*, Reading, MA: Addison-Wesley.

Wired News. 1999. "Sub Pop Enters MP3 Domain," February 24 (available at www.wired.com/news/culture/0,1284,18107,00.html; accessed January 10, 2008).

Worlton, J. 1998. "Some Patterns of Technological Change in High Performance Computers," in *Proceedings of Supercomputing 1988*, Orlando, FL, November 14-18, Los Alamitos, CA: IEEE Computer Society Press, pp. 312-320.

About the Authors

Gediminas Adomavicius is currently a Digital Technology Center Associate Professor of Information and Decision Sciences at the Carlson School of Management, University of Minnesota. He received his Ph.D. in Computer Science from New York University. His research has been published in several leading Information Systems and Computer Science journals, including *Information Systems Research*, *ACM Transactions on Information Systems*, *IEEE Transactions on Knowledge and Data Engineering*, *INFORMS Journal on Computing*, and *Data Mining and Knowledge Discovery*. He received the NSF CAREER award in 2006 for his research on personalization technologies.

Jesse C. Bockstedt is an assistant professor in the Information Systems and Operations Management unit of the School of Management at George Mason University. He received his Ph.D. in Information Systems from the University of Minnesota. He research has been published in *Communications of the ACM*, *IEEE Transactions on Knowledge and Data Engineering*, *International Journal of Electronic Commerce*, and *Information Technology and Management*. His research interests include technology evolution, data mining and visualization, the use of Internet technologies by consumers, and the impact of new IT on consumers and products.

Alok Gupta is the department chair and Carlson School Professor of Information and Decision Sciences at the University of Minnesota. He received his Ph.D. in MSIS from the University of Texas, Austin, in 1996. His research has been published in various information systems, economics, and computer science journals such as *Management Science*, *Information Systems Research*, *MIS Quarterly*, *Communications of the ACM*, *Journal of MIS*, *Decision Sciences*, *Journal of Economic Dynamics and Control*, *Computational Economics*, *Decision Support Systems*, *International Journal of Electronic Commerce*, *IEEE Internet Computing*, and *Journal of Commerce*. He received NSF CAREER award in 2001 for his research on online auctions. He serves on the editorial boards of *Management Science*, *Information Systems Research*, *Journal of MIS* and *Decision Support Systems* and various national an international research centers.

Robert J. Kauffman is the W. P. Carey Chair in Information Systems at the W. P. Carey School of Business, with joint appointments in IS, Finance, and Supply Chain Management, as well as the School of Computing and Informatics, at Arizona State University. His M.A. is from Cornell, and his M.S. and Ph.D. are from Carnegie Mellon. His research interests span the economics of IS, technology adoption, competitive strategy and technology, IT value, and theory development and empirical methods for IS research. He has won numerous research awards, including a 2006 "outstanding research contribution award" for the best paper of the year in *IEEE International Society for Engineering Management* in 2005, and a 2007 "best paper award" for an article published in 2006 in the *Journal of the Association for Information Systems*. His articles appear in *Management Science*, *Organization Science*, *Information Systems Research*, *Journal of MIS*, *MIS Quarterly*, *Decision Sciences*, *Information Technology and Management*, *Communications of the ACM*, and other leading journals.

Appendix

Interview Questions

PART 1: General questions on IT landscape analysis, etc.

Based on your experience, how are technologies chosen in the information technology (IT) investment and development decision processes? How do organizations typically go about analyzing the IT landscape to discover potential technologies to invest in or adopt?

How important do you think historical technology analysis is for making decisions about IT investment/development? (Rate 1-5 and then explain.)

1	2	3	4	5
Very unimportant	Somewhat unimportant	Neither important nor unimportant	Somewhat important	Very important

How important do you think evaluating the current landscape of IT is for making investment/development decisions? (Rate 1-5 and then explain.)

1	2	3	4	5
Very unimportant	Somewhat unimportant	Neither important nor unimportant	Somewhat important	Very important

How important do you think predicting the future landscape of IT (technology forecasting) is for making decisions about IT investment/development? (Rate 1-5 and then explain.)

1	2	3	4	5
Very unimportant	Somewhat unimportant	Neither important nor unimportant	Somewhat important	Very important

What types of techniques, methods, or tools have you or your company/organization used (or are familiar with) to analyze the past, current, and future landscape of information technology?

Based on your experience, what are common challenges in IT landscape analysis, forecasting, and the IT investment/development decision-making process? In what ways, if any, do you think existing tools/methods/techniques could be improved?

How effective do you feel existing tools/methods/techniques are for analyzing the technology landscape and performing technology forecasting? (Rate 1-5 and then explain.)

1	2	3	4	5
Very ineffective	Somewhat ineffective	Neither effective nor ineffective	Somewhat effective	Very effective

PART 2: Overview of the proposed artifacts

In this portion of the interview, the interviewer presented the proposed constructs and methodologies of the IT ecosystem model to the participant and answered any questions the participant had about the IT ecosystem model and its use. The presentation covered: (1) the business problem the proposed artifacts are trying to address and motivation for this research, (2) an overview of the IT ecosystem model, (3) the definition of the roles, paths of influence, and patterns of technological change, (4) the methodology for identifying a specific IT ecosystem and creating a state diagram of the historical technological change within an ecosystem with the qualitative digital music and quantitative Wi-Fi technology examples. Tables 1, 2, and 3 and Figures 3, 4, 7, and 9 were used in the presentation of the IT ecosystem model to the interview participant.

PART 3: Questions on the utility and use of the proposed artifacts

How effective do you feel the proposed methodology is in providing a new technique for identifying and analyzing patterns in technology evolution? (Rate 1-5 and then explain.)

1	2	3	4	5
Very ineffective	Somewhat ineffective	Neither effective nor ineffective	Somewhat effective	Very effective

Do you feel the use of the component, product, and infrastructure roles help in understanding the nature of technology evolution? If so, how do you think they create value?

Are there any missing or unnecessary roles? Please explain.

Do you feel the method for identifying relationships between technology roles provides better understanding about the technology evolution? Please explain.

Do you feel the classification of paths of influence is complete? Please explain.

What do you think are the strengths and weaknesses of the technology roles and paths of influence?

Do you feel the method (qualitative and quantitative) for identifying patterns of technology evolution is sound? Please explain.

Are there any assumptions or steps in the method that seem unreasonable? Please explain.

Do you feel the information generated using the proposed methodology is useful? Please explain.

Do you feel the graphical representation of trends is useful? Please explain.

What do you think are the strengths and weaknesses of the information generated by the proposed methodology?

What is your general reaction to the proposed methodology and its utility for analyzing technology trends?

If you feel the proposed methodology and approach is useful, how is it useful for organizations?

Do you feel the proposed conceptual approach and methodology would benefit organizations making IT forecasts? Please explain.

Do you feel the proposed conceptual approach and methodology would aid in the IT investment/development decision making process? Please explain.

Overall, what do you feel are the strengths and weaknesses of the proposed conceptual approach and methodology?

Who do you think is the most appropriate user of the proposed conceptual approach and methodology, if any? Please explain.