Information Technology Innovations: General Diffusion Patterns and Its Relationships to Innovation Characteristics

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***Abstract*—While many scholars of organizational innovations have examined characteristics of innovations such as relative advantage and complexity and how they facilitate the adoption of an innovation by organizations, others have used mathematical models to fit diffusion patterns. In this study, we attempt to integrate these two areas of inquiry and explore the possibilities to predict diffusion patterns based on characteristics of the innovation and the adopting entities. Based on a cross-sectional sample of 313 large American firms, 20 information technology (IT) innovations were examined and their diffusion patterns assessed with respect to models that espoused internal and external influence. The mixed influence model (Bass model) was chosen as a robust common representation for the set of diffusion patterns. However, the external influence as represented by the coefficient of innovation was found to be extremely small and the internal influence dominates for all innovations. The other two parameters of the model, the saturation level and the coefficient of imitation, which represents internal influence, were then used to perform a cluster analysis. Five clusters of technologies emerged, and the potential relationships between their innovation characteristics and diffusion patterns were explored. Rigorous examination of these potential relationships by future researchers may result in practical methods for predicting patterns of IT innovation diffusion based on innovation and technology characteristics.**

***Index Terms*—Information technology innovations, innovation characteristics, innovation diffusion models, mathematical modeling, prediction of innovation diffusion patterns, technological forecasting, technological innovation diffusion.**

I. INTRODUCTION

THE STUDY of organizational innovation has accumulated an impressive body of theories and empirical results over several decades of intensive research [9], [44], [45]. As our knowledge-based economy increasingly depends on more and better information [11], the introduction and successful adoption of new information technologies (IT) by business firms has become a critical element of their competitive strategy [40]. Framing the introduction of new IT as organizational innovation [21], [34], information systems (IS) researchers have studied the adoption and diffusion of modern software practice [58]–[60], spreadsheet software [5], customer-based interorganizational systems [15], database management systems [16], electronic data interchange [42], and IT in general [25]. Most of these studies focus on factors and innovation attributes that can predict adoption behavior, an area that has received focused attention by many innovation researchers [55]. More recently, innovation research within the IS field has attempted to build theories that integrate IS innovation with the general innovation theories. Swanson's tri-core theory [53], for example, extends Daft's [8] dual-core theory of technical and administrative innovation in organizations by incorporating several types of IS innovation which constitute the third core. A recent study by Grover, Fiedler, and Teng [17] has provided partial empirical support for Swanson's theory.

Another central theme of the innovation field has been the mathematical modeling of innovation diffusion for different types of organizational innovation and under different assumptions. One recurring finding is the existence of a bell-shaped curve when frequency of adoption is plotted over time, and a general S-shaped curve when the cumulative number of adopters is plotted [24], [30]. At first, the adoption rate is very low, and only few members of the social system adopt the innovation. After a period of time, the rate of adoption will increase sharply until the peak of the bell-shaped curve is reached. After that point, the number of adoptions decreases. The cumulative number of adoptions then spreads asymptotically to a saturation level, where the maximum number of adopters is reached. At this point, the diffusion is complete. A large variety of diffusion models have been developed by researchers, reflective of different forms of the S-curve for different innovations [24], [36]. The most widely used models for innovation diffusion include the external influence model, the internal influence model as represented by the logistic curve, the Gompertz function and the Bass model [4], [36].

A. Research Objectives and Contribution

While studies in organizational innovation have contributed to our understanding of IT adoption behavior, previous empirical modeling efforts have improved our understanding of IT diffusion patterns. A number of studies on modeling diffusion of non-IT technologies examined more than one innovation [2], [3], [12], [14], [31], but modeling efforts for IT tend to focus on just a single innovation [18], [28], [29]. [57]. As discussed by Tornatzky and Klein [55], one important criterion for an "ideal" innovation characteristics study is to examine more than one innovation, as single innovation studies are not sufficiently

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robust to permit generalization to a population of innovations. In this study, our first objective is to find a common representation of innovation diffusion patterns across a large variety of information technologies. This would be a significant step in understanding the diffusion process common to IT innovations, as different models imply very different diffusion dynamics. The internal influence model, for example, portrays an imitation and learning dynamic among the society of potential adopters, while the external model depicts a dominating guiding force from outside [36]. As a result, our knowledge of general IT diffusion patterns would be greatly improved, better preparing us to undertake the critical step toward developing a general theory of IT innovation and diffusion. To explore this possibility, our second research objective is to identify different classes of information technologies having similar diffusion patterns in terms of the parameters of their diffusion curves. These parameters are related to critical dimensions of the dynamics of the diffusion process. The coefficient of imitation, for example, pertains to how swiftly an innovation spreads through contacts among potential adopters. If two innovations have similar diffusion patterns and spread among potential adopters with roughly equal speeds, one would anticipate the possibility that they are also similar in terms of innovation characteristics such as relative advantage and complexity. Thus, this tentative classification of information technologies based on their diffusion patterns would provide the empirical data base for us to address the third research objective: to explore the relationships between innovation characteristics of the information technologies and their general diffusion patterns.

Accomplishing these three research objectives would result in significant contributions for both research and practice. While scholars of organizational innovation have examined characteristics of innovations such as relative advantage and complexity and how they facilitate the adoption of an innovation [55], others have used mathematical models to fit diffusion curves [24], [36]. With results from this study, we may begin to integrate these two areas of inquiry and undertake the initial step toward linking an information technology's innovation characteristics to its diffusion pattern. The facilitation and planning of innovation is a critical element of managing organizational change [51]. In the last stage of the 20th century, IT has become the prime driving force for organizational innovation. The latest wave of business innovation, such as business process reengineering [54] and electronic commerce, are often enabled by information technologies such as the Intranet, Extranet, telecommunication, and databases [10]. By discovering the potential relationships between these information technologies' innovation characteristics and their diffusion patterns, we can begin to understand the dynamics of IT-driven innovations in organizations and be able to plan and manage them more effectively.

B. Information Technologies Studied

We will begin by examining the overall diffusion pattern of a spectrum of information technologies in the economy. This includes 20 contemporary hardware and software technologies drawn from various technological studies [52]:

1) fourth generation languages (4GL);
2) computer-aided design/computer-aided manufacturing (CAD/CAM);
3) teleconferencing;
4) computer-aided software engineering (CASE);
5) client/server;
6) electronic data interchange (EDI);
7) e-mail;
8) executive information systems (EIS);
9) expert systems;
10) FAX;
11) imaging;
12) workstations;
13) spreadsheet programs;
14) PCs;
15) object oriented programming (OOP);
16) mini-computer;
17) mainframe-computer;
18) large-scale relational databases;
19) local area network (LAN);
20) integrated service digital network (ISDN).

One consideration in selecting the set of IT innovations is the need to have sufficient elapsed time since the inception of the technology to allow the fitting of the entire curve. Some recent innovations such as those involving the World Wide Web (WWW) and e-commerce were, therefore, not included.

II. Alternative Models of Innovation Diffusion

To accomplish the first research objective, we will fit a number of alternative diffusion models for all 20 ITs and attempt to identify one of these models as a common representation. Among many models of innovation diffusion, four widely used ones are of primary interest to us:

1) external influence model;
2) internal influence model, as represented by the logistic curve;
3) Gompertz function;
4) Bass model.

These models belong to the group of fundamental diffusion models, and a brief overview of the four models based on the work of Mahajan and Peterson [30] and Meade and Islam [36] is given. All of these models have one thing in common: the rate of diffusion is proportional to the number of potential adopters at a given time t. It can be expressed with the following equation:

$$\frac{dN(t)}{dt} = g(t)(m - N(t)) \tag{1}$$

where

- $N(t)$ number of potential adopters that has adopted the innovation at time t $(0 \leq N(t) \leq m)$;
- m total number of potential adopters in the social system, the saturation level;
- $g(t)$ coefficient of diffusion.

The coefficient of diffusion $g(t)$ can be viewed as a function of the number of previous adopters. Depending on $g(t)$, three types of fundamental diffusion models can be distinguished.

A. *External Influence Model:* $g(t) = a$

The external influence model assumes that no communication exists between the members of a social system. All influence comes from the outside, e.g., from mass media or consulting companies. This influence is represented by the constant a, the influence of "change agent." That is any influence other than a prior adoption. Substituting $g(t)$ into the fundamental diffusion model (1) yields the rate of diffusion:

$$\frac{dN(t)}{dt} = a(m - N(t)). \tag{2}$$

Integrating (2) yields the cumulative form of the external influence model

$$N(t) = m(1 - \exp(-at)). \tag{3}$$

The external diffusion model has a constant growth pattern. Its use is restricted to cases where members of a social system have no contact with each other.

B. *Internal Influence Model:* $g(t) = bN(t)$

In contrast to the external influence model, the internal influence model is based on the assumption that diffusion occurs only through contacts among members of the social system. Therefore, it is considered as representing a pure imitation diffusion model. The constant b can be defined as a coefficient of imitation or internal influence. Substituting $g(t)$ in (1) by $bN(t)$ yields the rate of diffusion

$$\frac{dN(t)}{dt} = bN(t)(m - N(t)). \tag{4}$$

Integration of (4) yields the distribution function, the logistic-curve

$$N(t) = \frac{1}{\frac{1}{m} + c\exp(-bt)}. \tag{5}$$

Closely related to the logistic curve is the Gompertz-function. It assumes that the rate of adoption is a function of the logarithm of the number of potential adopters

$$\frac{dN(t)}{dt} = bN(t)(\ln(m) - \ln(N(t))). \tag{6}$$

The cumulative adopter distribution of this model is

$$N(t) = m\exp(-c\exp(-bt)). \tag{7}$$

While the logistic curve is symmetrical around the point of inflection[1] at 50% of potential adopters, the Gompertz curve is nonsymmetrical. Its point of inflection is reached when 37% of the potential adopters have adopted an innovation.

C. *Mixed Influence Model:* $g(t) = a + bN(t)$

The mixed influence model, introduced by Bass [4], is a combination of both the external and internal influences. It assumes that potential adopters of an innovation are influenced by internal influences among members of the social system and also by external influences. It is widely used in the marketing area for the forecasting of durable consumer goods. Its rate of diffusion can be yielded by substituting $g(t)$ by $a + bN(t)$ in (1)

$$\frac{dN(t)}{dt} = (a + bN(t))(m - N(t)). \tag{8}$$

Integrating (8) yields the cumulative adopter distribution of the mixed influence model

$$N(t) = m\frac{1 - \exp(-t(a+b))}{1 + \frac{b}{a}\exp(-t(a+b))}. \tag{9}$$

The mixed influence model is symmetric around the point of inflection between 0% and 50% of potential adopters. The parameter a, which represents external influence, is known as the coefficient of innovation and b, which represents internal influence, the coefficient of imitation. The roles of the two coefficients were demonstrated by marketing researchers Sultan, Farley, and Lehmann [47] in a meta-study of 213 innovations. When compared to the U.S., for example, the coefficient of innovation (a) is generally higher in Europe since most of the innovative products originated in the U.S., which is the source of external influence for European consumers. In general, however, the coefficient of innovation is small (average .03) compared to the coefficient of imitation (average .38), suggesting that the diffusion of these products is largely a process of imitation rather than innate innovativeness of consumers [47].

D. *Application of Diffusion Models on IS Innovation*

We have briefly described four widely used innovation diffusion models. Some of these models have been applied to examine IS innovation diffusion patterns. These studies have been conducted at several levels:

1) at the level of intrafirm diffusion, i.e., diffusion of innovation within an organization;
2) interfirm diffusion at the industry level;
3) overall diffusion of an innovation throughout the economy.

For intrafirm diffusion, one example is the work of Astebro [1], who modeled the diffusion of an e-mail system in several departments within Volvo Car Inc. using the Bass model. The Bass model fits the data well for all departments. Except for one department (product development), the external influence was very low (≤ 0.0055). Brancheau and Wetherbe [5] studied the diffusion of spreadsheet software among the finance and accounting departments of 21 companies. The logistic function resulted in a very good fit for the overall distribution of adopters, but for the diffusion within each of the companies the logistic curve had a good fit in only nine cases. For interfirm diffusion at the industry level, Liberatore and Breem [28] have examined the diffusion of digital imaging among banking and insurance companies. While the external influence and the Bass model were rejected, the logistic curve gave the best results.

Patterns of overall diffusion of IT innovations throughout the economy have also been studied. Loh and Venkatraman [29], for example, modeled the diffusion of IS outsourcing using three fundamental diffusion equations: internal, external, and mixed influence models. The data were best fitted by the logistic func-

[1] The inflection point occurs where the rate of growth of users is the highest, and the rate begins to decline subsequently (i.e., the second derivative of the curve is 0).

tion also. However, a re-evaluation of their research by Hu *et al.* [19] showed that the diffusion of outsourcing could be best described by a mixed influence model. Gurbaxani [18] examined the overall diffusion of BITNET, a predecessor of the Internet, among universities using the various fundamental diffusion models and found that the logistic model had the best fit. Wang and Kettinger [57] also used the logistic curve to predict the diffusion of cellular communication. The global diffusion of the Internet, studied recently by Rai *et al.* [41], can best be represented by an exponential model.

III. Research Method and Measurements

To accomplish the three research objectives, we have conducted an empirical field study by gathering data through a research questionnaire. In selecting the survey respondents, we followed the guidelines prescribed by Huber and Power, [20] who recommended that the individual most knowledgeable about the subject matter should be selected as the respondent in the case when only one respondent per unit is solicited. As the instrument includes questions related to IT and the IS function, senior IS executives were chosen as survey respondents rather than CEOs or other top managers.

A. Measurements

For each of the 20 IT innovations, two key measures were taken: 1) the year when the organization adopted the innovation for the first time; and 2) the diffusion or penetration of the innovation within the organization. While many innovation measures focus on the number of adopters within the organization [9], it is important to normalize this number based on the number of potential adopters. For instance, CASE technology might not have significant penetration outside the IS group. Therefore, the following item assesses the "infusion" level of each IT based on a ratio (percentage) scale:

For those employees who can benefit from this IT, what percentage are using[2] *it?*___%

Additionally, the questionnaire contained a series of general questions regarding the organization and the respondent.

B. Sample and Administration

The survey instrument was developed and pretested on MIS academics for clarity and focus. The unit of analysis for this research is an organization which was described in the questionnaire as "the corporation, business unit, subsidiary or division that is served by your IS department." The final questionnaire was administered to a sample of 900 IS executives drawn from a database of 5000 IS executives in the U.S. provided by an information service firm. The sample was selected on the basis of revenue (greater than $50 million).

Two mailings were sent out one month apart. Respondents were encouraged to call with any question they had regarding the instrument. To provide additional incentive for completing the questionnaire, the respondents were given the opportunity to choose one of several charitable organizations for the researchers to make a $2.00 donation on their behalf. Of the 900 initial mailings, 45 were returned as undeliverable. A total of 313 completed responses were received, yielding an effective response of 36.6%. This response rate compares very favorably to many mail surveys reported in the literature.

[2]Use refers to whether the technology is being used, and no distinction is made regarding the depth of use. The assumption is that users are using it beyond a fair trial point.

TABLE I
INDUSTRY PROFILE AND SIZE OF RESPONDING ORGANIZATIONS

Industry Profile of Responding Organizations

Industry	Frequency	Percentage
Banking/Financial Service/Insurance	79	25.3%
Manufacturing	78	24.9%
Healthcare	37	11.8%
Retailing/Wholesale	33	10.5%
Business/Information Services	22	7.0%
Utility/Transportation	20	6.4%
Media	11	3.5%
Other	20	6.4%
Not Indicated	13	4.2%
TOTAL	313	100%

Size of Responding Firms

Number of Employees	Frequency	Percentage
<1000	66	21.1%
1,000-2,500	84	26.8%
2,500-5000	58	18.5%
5,000-10,000	34	10.9%
10,000-25,000	31	9.9%
>25,000	21	6.7%
Not Indicated	19	6.1%
TOTAL	313	100%

C. Sample Characteristics

Table I contains a summary of the industry affiliation of responding firms. As can be seen, a wide variety of industries were represented. The top two industry categories—financial service and manufacturing—which account for over half of the respondents, are followed by healthcare and retail/wholesale. Also seen in Table I, the sample is well representative of a variety of firm sizes, with the average size being 9519, and the median 2500 employees. In addition, we checked early adopters against late adopters and found no significant difference in firm size, providing significant indication that characteristics of the responding firms closely match those of the sampling frame.

Over 80% of the participating IS executives had worked in his/her current company for at least five years. The average is more than 12 years. This adds to the confidence that the respondents have reliable sources of information on the timing of the first introduction of the technologies chosen. Table II shows the age of the participating firms. This information is important to the analysis of research results, as a firm could not possibly adopt an IT innovation before the company was founded. Thus, when computing the cumulative percentage of firms that have adopted a given IT by a certain year, we considered only those companies that existed at the time. This adjustment, however, was very minor. As indicated in Table II, more than 80% of the firms in the

TABLE II
AGE OF PARTICIPATING FIRMS

Year Company was Founded	Number of Companies	Percentage
Prior to 1950	170	59.4%
1950-1959	18	6.3%
1960-1969	30	10.5%
1970-1979	29	10.1%
1980-1989	34	11.9%
1990-1991	5	1.7%
Total:	286*	100%

* 27 companies did not answer that question

TABLE III
INNOVATION PROFILES

Information Technology Innovation	Number of Adopters	Adopters among Sample Firms (%)	Average penetration within companies
4GL Languages	200	63.90%	48.75%
CAD/CAM	117	37.38%	70.36%
CASE	115	36.74%	34.48%
Client/Server	186	59.37%	38.76%
EDI	167	53.35%	48.93%
Email	256	81.75%	63.64%
Executive Information Systems	114	36.33%	35.81%
Expert Systems	87	27.73%	25.20%
FAX	293	93.61%	84.74%
Imaging	125	39.79%	32.03%
ISDN	66	21.03%	64.46%
LAN	288	92.01%	63.44%
Large Scale Relational Databases	171	54.63%	54.07%
Mainframe	249	79.55%	87.37%
Mini-Computer	252	80.51%	77.02%
OOP	78	24.92%	27.91%
PC	306	97.76%	76.31%
Spreadsheet	305	97.44%	75.15%
Teleconferencing	147	46.96%	52.21%
Workstation	175	55.91%	57.07%

sample were founded before 1980, and most of the technologies we studied began to diffuse during and after the 80s.

Table III describes the innovation profile for each innovation. While the second column provides the percentage of organizations that had adopted each innovation, the average penetration of each innovation within the organizations that had adopted the innovation is shown in the third column. The percentage of adoption ranges from 24.92% for OOPs to 97.76% for PCs. For average intrafirm penetration, the percentage ranges from 25.2% for expert systems to 84.74% for fax. Previous innovation studies focused either on the intrafirm or the interfirm diffusion of an innovation. In this study, we can examine the relationship between the two phenomena by calculating the correlation between the percentage of companies that had adopted an innovation and the average penetration within the companies. This correlation turns out to be very high ($r = 0.727$), and is significant at the 0.01 level. Thus, if a new IT appeals to a large number of organizations and reaches a high level of diffusion among the companies, one can expect this IT will also achieve high penetration within these companies, and vice versa. This result suggests the possibility that similar forces drive the diffusion within companies and among companies.

IV. FITTING ALTERNATIVE DIFFUSION MODELS

To achieve our first research objective, we begin the data analysis on the year of adoption data for the 20 information technologies. We used the Levenberg-Marquardt method of nonlinear regression to fit the four alternative diffusion models:

1) external influence model;
2) internal influence model (logistic curve);
3) internal influence model (Gompertz curve);
4) mixed influence model (Bass model).

Unlike previous studies where only some parameters are estimated, we estimated all parameters including the maximum adopters. The degrees of fit of the four models were measured by the R^2-values, which represented the proportion of variation fitted by the model. Table IV shows the R^2-values for the 20 innovations resulting from all four models. According to the meta-analysis results reported by Sultan *et al.* [47], model parameters such as coefficients of innovation and imitation are affected by the estimation methods, but the magnitudes of the differences are small. Nonlinear procedures like the one used in the current study lead to slightly lower estimates of the model parameters compared to the ordinary least square (OLS) procedure [47]. Thus, we are confident that we did not overestimate the coefficients of innovation and imitation for the 20 diffusion models.

The results indicate that, except for OOP, the highest fit among the four models is over 99% for all IT innovations. The relatively inferior fit for OOP can be explained by the late start of the diffusion at the beginning of the 1990s. At the time of the study, only 25% of the companies had adopted OOP. This makes the estimation for the further diffusion of OOP very difficult. For this reason, OOP is excluded from further analysis and we will analyze the remaining 19 innovations.

As can be seen in Table IV, the external influence model had the worst fit of all models. In all 20 cases, it overestimated the number of potential adopters (i.e., exceeded the sample size), and the number of potential adopters had to, therefore, be fixed to 100%. We conclude that the external influence model is not an appropriate model for modeling the diffusion of IT innovations.

Compared to the external model, all three other models result in substantially better fits. For all technologies except mainframe, the Gompertz model showed the lowest fit among the three models. For 14 of the 19 innovations, the logistic curve has the best fit.[3] However, the differences in R-square between the logistic model and the Bass model are extremely small (average difference for the 19 innovation= 0.025). In a meta-analysis of 213 diffusion model applications, Sultan *et al.* [47] concluded that the broader Bass model, which includes both the coefficient of innovation (the external influence) and the coefficient of imitation (the internal influence) should be used to avoid what may be an important implicit restriction on parameters. Thus,

[3]Peak time for logistic curve $= (\ln(c) + \ln(m))/\ln(b) +$ year of first adoption

TABLE IV
FITTING FOUR ALTERNATIVE DIFFUSION MODELS (R-SQUARES)

IT Innovation	Diffusion Model #			
	External-Influence Model	Internal-Influence Model: Logistic Curve	Internal-Influence Model: Gompertz Curve	Mixed-Influence Model: Bass-Model
4GL Languages	76.49%*	99.88%	99.74%*	99.88%
CAD/CAM	83.00%*	99.38%	99.36%	99.42%
CASE	75.30%*	99.95%	99.76%	99.94%
Client/Server	51.45%*	99.78%	99.26%*	99.77%
EDI	54.76%*	99.69%*	98.52%*	99.68%*
Email	63.34%*	99.69%*	98.65%*	99.68%*
Executive Information Systems	58.92%*	99.79%	99.57%*	99.78%
Expert Systems	74.68%*	99.52%	99.44%	99.53%
FAX	72.27%*	99.60%*	98.36%*	99.55%*
Imaging	46.07%*	99.88%	99.68%*	99.88%
ISDN	72.34%*	99.33%	99.11%*	99.27%
LAN	62.35%*	99.88%*	99.08%*	99.88%*
Large Scale Relational Databases	62.02%*	99.57%	98.80%*	99.55%
Mainframe	89.11%*	99.37%	99.63%	99.48%
Mini-Computer	86.38%*	99.59%	99.59%*	99.66%
OOP	40.77%*	98.05%*	96.82%*	98.05%*
PC	76.86%*	99.91%	99.69%*	99.92%
Spreadsheet	69.52%*	99.84%	99.61%*	99.84%
Teleconferencing	64.35%*	99.56%*	98.35%*	99.52%*
Workstation	61.12%*	99.23%*	97.85%*	99.20%*

* Number of maximum adopters had to be fixed to 100%
\# All models are significant at $p < .05$
Model with the best fit

the generalized logistic curve, i.e., the Bass model is selected as a robust common representation for all 19 innovation patterns.[4]

A. The Bass Model

The Bass model fit for three of the information technologies (a computing, communication, and developmental IT) included in this study—PC, e-mail, and CASE—are shown in Fig. 1.[5] As can be seen, while a modest portion of potential user organizations eventually adopted CASE, PC reached a maximal level of saturation. In Fig. 2, the diffusion of three generations of computing technology is portrayed. Note that eventually both mainframe and mini-computer achieved about the same level of saturation, but the mini curve has a steeper slope than mainframe, indicating that its diffusion among adopters was faster. In terms of the Bass model parameters, this means that the mini curve has a higher coefficient of imitation than mainframe. For PC, on the other hand, both the saturation level and the coefficient of imitation are very high.

[4]It should be noted that even for the mainframe computer where the Gompertz model has the best fit, its R-square result is only 0.15 higher than the Bass model.

[5]Model fitting was conducted using the software DataFit V. 6.1 from Oakdale Engineering.

The years of inflection[6] of the innovations are plotted in Fig. 3. As can be seen, the inflection year for most innovations is between 1989 and 1993. The mainframe computer as the oldest technology in this study had its point of inflection in 1969, followed by the mini computer in 1981. These and all other IT inflection years are consistent with expectations, adding to the face validity and representativeness of the sample data.

B. Discussion and Interpretation

Our first objective is to find a common representation for the diffusion patterns of a large variety of information technologies. The results, as shown in Table IV, indicate that the external model has the worst overall fit. This can be interpreted from two perspectives. First, the U.S. is a pluralistic market economy without a dominating guiding force from government or other authoritative controlling entities that provide a constant source of "external" influence. Secondly, new information technologies introduced over the past decades are fundamentally different from the industrial age technologies, and there has been a void of meaningful past experience to serve as a guide to innovation adoption and implementation.

[6]The year of inflection is at the inflection point of the diffusion curve.

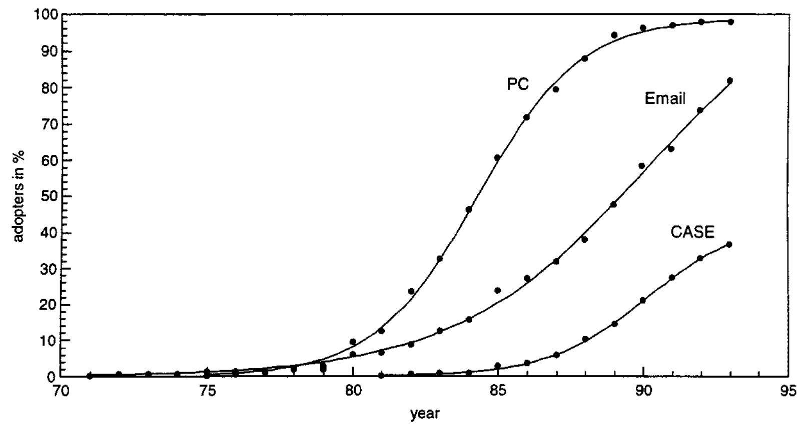

Fig. 1. Bass diffusion curves of three IT innovations.

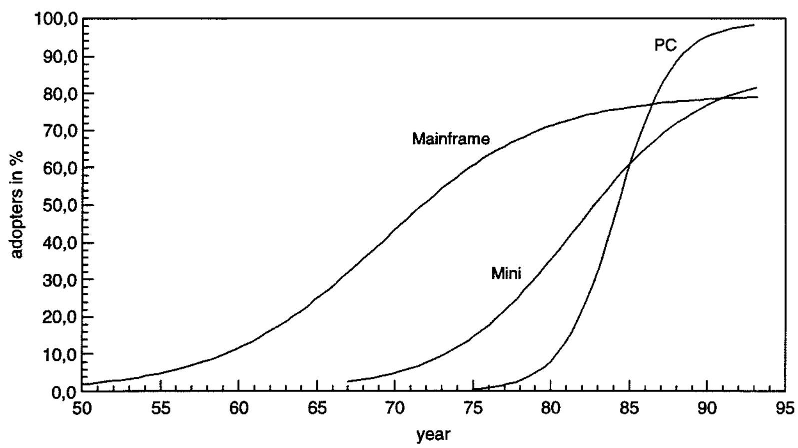

Fig. 2. Bass diffusion curves of successive generations of computer technologies.

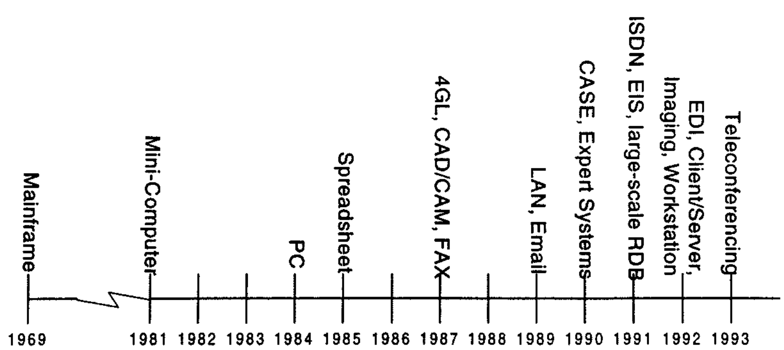

Fig. 3. Year of inflection of the innovations.

As indicated earlier, the best choice for a robust common representation of the set of IT innovation diffusion patterns is the mixed influence model as depicted by the Bass curve. Estimated parameters for the curve are listed in Table V for all 19 innovations. As can be seen, the parameters for external influence (coefficient of innovation) are extremely small (between 0.0001 and 0.0062), and the internal influence dominates. This is not unexpected given the poor fit of the external influence model. In addition, these results are consistent with the meta-analysis findings of Sultan *et al.*, [47] which revealed extremely low coefficients of innovation for durable consumer products in the U.S. (in contrast to Europe) due to the fact that European consumers had rather strong external influence from the U.S. As all information technologies included in our study were introduced first in the U.S., there was a lack of external source of influence and the diffusion of these technologies was basically an imitation process through contacts among members of the social system. The dominance of the internal influence may also be attributed to the competitive environment. Over the last decades, businesses in this country have been using IT as a major competitive weapon [40], and the pressure to imitate quickly has been intense. There is em-

TABLE V
BASS CURVE: PARAMETER ESTIMATIONS

Information Technology Innovation	Bass Curve Parameters #			
	a	b (coefficient of imitation)	m (in %) (Saturation level)	Year of Inflection
4GL Languages	0.0037 (13.43)	0.3089 (25.76)	78.38 (33.52)	1987
CAD/CAM	0.0048 (5.88)	0.3186 (11.79)	43.50 (19.69)	1987
CASE	0.0029 (10.35)	0.5738 (29.09)	44.06 (40.40)	1990
Client/Server	0.0001 (3.12)	0.6630 (15.68)	87.91 (12.30)	1992
EDI	0.0002 (8.37)	0.2980 (47.24)	100.00*	1992
Email	0.0008 (8.37)	0.3303 (40.47)	100.00*	1989
Executive Information Systems	0.0003 (5.08)	0.4289 (19.79)	51.29 (16.07)	1991
Expert Systems	0.0029 (5.21)	0.4283 (10.59)	37.42 (10.24)	1990
FAX	0.0026 (6.55)	0.3980 (26.62)	100.00*	1987
Imaging	0.0000 (4.65)	0.5189 (24.64)	67.50 (14.07)	1992
ISDN	0.0026 (4.95)	0.4277 (7.68)	34.75 (5.11)	1991
LAN	0.0006 (6.94)	0.6863 (42.48)	100.00*	1989
Large Scale Relational Databases	0.0006 (5.81)	0.3074 (14.41)	87.39 (9.53)	1991
Mainframe	0.0062 (10.10)	0.1709 (20.08)	80.68 (82.74)	1969
Mini-Computer	0.0035 (11.92)	0.2043 (16.29)	89.41 (40.08)	1981
PC	0.0032 (9.72)	0.5519 (36.37)	99.09 (140.30)	1984
Spreadsheet	0.0009 (5.49)	0.5454 (27.31)	99.41 (92.67)	1985
Teleconferencing	0.0008 (9.77)	0.2344 (38.30)	100.00*	1993
Workstation	0.0005 (6.74)	0.2418 (31.20)	100.00*	1992

* value was fixed to 100%

\# t-values for the parameters are in brackets. all significant at $P < .05$

pirical evidence that has demonstrated first mover advantage in gaining market power through innovative applications of new ITs, [39], as well as high levels of imitation in industries with strategic applications [49]. In addition, our results are also consistent with prior work, which revealed that industrial/medical innovations have higher coefficients of imitation than other innovations as the adopting units may be forced by competitive pressures to imitate quickly [47].

V. IDENTIFYING CLASSES OF INFORMATION TECHNOLOGIES

Our second research objective is to identify different classes of information technologies in terms of the parameters of their diffusion curves. The estimated parameters of the Bass curve for the 19 IT innovations, as summarized in Table V, indicate that the parameters vary greatly. For example, CASE has a very high coefficient of imitation and a very low saturation level. In contrast, e-mail has a saturation level of 100% and a relatively low coefficient of imitation, similar to fax. Previous modeling studies have attempted to classify different innovations based on parameters of their diffusion curves [14], [31]. For this study, given the negligible coefficients of innovation (the coefficient a), parameters such as saturation level (m) and coefficient of imitation (b) represent critical diffusion characteristics, and a classification of information technologies based on these two parameters would help us to identify different patterns of IT innovation diffusion and move us further toward developing theories of IT innovation and diffusion.

A. Cluster Analysis

Cluster analysis was conducted using the SPSS software to explore options for grouping the various ITs. The objective of the cluster analysis is to find homogenous groups and to maximize the difference between the groups. Unlike most parametric statistical techniques, cluster analysis does not explicitly provide a clearly acceptable or unacceptable solution. Sharma [50] recommends that one should "use the various methods, compare the results for consistency, and use the method that results in an interpretable solution" [50, p. 217]. As the two variables for the cluster analysis, the parameters b (coefficient of imitation) and m (saturation level) of the Bass curve, were measured on different scales, they were standardized (mean$=$ 0 and standard

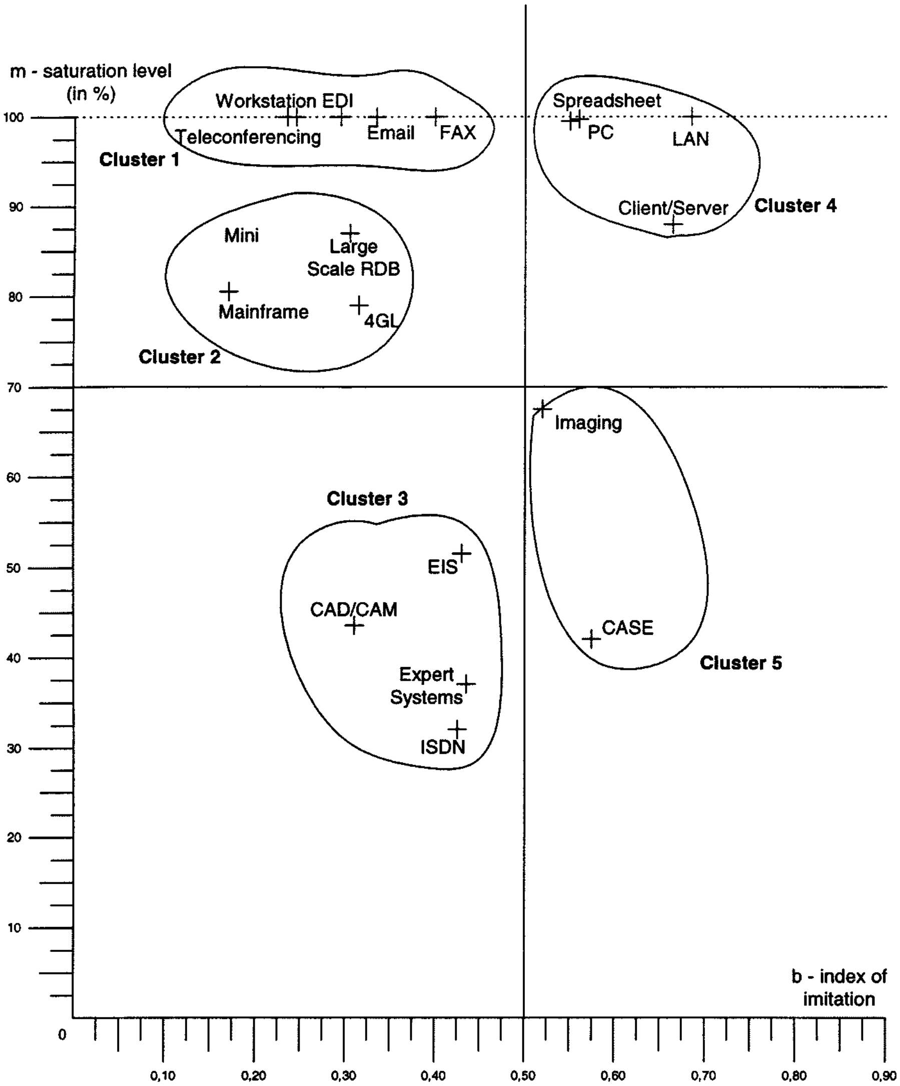

Fig. 4. Results of cluster analysis.

deviation= 1) before the analysis was attempted. The squared Euclidean distance measured the similarity between the innovations. As the study was exploratory in nature and the number of clusters was not predetermined, the hierarchical cluster analysis method was chosen. The clusters were estimated with the complete-linkage/farthest-neighbor method. This method typically identifies compact groups in which the observations are very similar and is less affected by the presence of noise or outliers in the data. Following the guidelines described by Sharma [50, p. 200], we attempt to detect a jump in standard deviation from one cluster solution to the next. This happens at three and at five clusters. In order to have more interpretable results, we decided to use the five-cluster solution as shown in Fig. 4.

Other solutions from hierarchical cluster analysis using methods such as nearest-neighbor or centroid produced similar results. However, some solutions combined cluster one and cluster two as one cluster and divided cluster five into two different clusters. It was felt that cluster one and two should be separated, as innovations in cluster one had to be fixed to the maximum saturation level of 100%, while those in cluster two had a maximum saturation level significantly lower than 100%. These considerations led us to choose the five-cluster solution in Fig. 4 over other solutions. Summary statistics for each of the clusters are provided in Table VI.

As the various clusters in Fig. 4 are vertically and horizontally aligned, we divided the space into six cells with three rows and two columns to facilitate discussion. The two columns indicate relatively slow or quick diffusion of the IT among its adopters. The three rows, on the other hand, indicate whether the IT was eventually adopted by a maximal proportion (90% or more), a large proportion (between 70% and 90%), or a moderate proportion (between 30% and 70%)[7] of potential adopters. The diffusion patterns of the five clusters, as summarized in Table VII, can thus be described as follows.

1) **Cluster 1**: information technologies that slowly diffused among a maximal proportion of potential adopters. These include workstation, teleconference, EDI, e-mail, and fax.

[7]For almost all the diffusion patterns, the predicted saturation levels (see Table V) are generally close to the actual levels of adoption (see Table III), and the curses essentially depict the entire diffusion process. The few exceptions to this are for EDI, teleconferencing, and workstations where the curves are relatively more predictive than descriptive.

TABLE VI
SUMMARY STATISTICS OF THE FIVE CLUSTERS OF IT INNOVATIONS

Cluster		Coefficient of imitation	Saturation level
1 (n=5): Workstations. Teleconferencing. Email. EDI. FAX	Mean:	0.3005	100.00
	Variance:	0.0046	0.00
	F-ratio:	0.1933	0.0000
2 (n=4): Mainframe. Mini. 4GL. large-scale RDB	Mean:	0.2479	83.97
	Variance:	0.0050	27.79
	F-ratio:	0.2135	0.0463
3 (n=4): Expert Systems. EIS. ISDN. CAD/CAM	Mean:	0.4009	41.74
	Variance:	0.0030	53.94
	F-ratio:	0.1277	0.0899
4 (n=4): PC. Spreadsheet. C/S. LAN and BPR	Mean:	0.6117	96.60
	Variance:	0.0054	33.72
	F-ratio:	0.2288	0.0562
5 (n=2): Imaging. CASE	Mean:	0.5464	55.78
	Variance:	0.0015	274.72
	F-ratio:	0.0640	0.4580
Total:	Mean:	0.4019	78.99
	Variance:	0.0236	599.76

TABLE VII
DIFFUSION PATTERNS OF INFORMATION TECHNOLOGIES

Proportion of potential adopters that adopted the technology eventually	Relative speed of diffusion among adopters of the technology	
	Low	High
Maximal	**Cluster 1:** workstation, teleconference, EDI, email, and fax.	**Cluster 4:** spreadsheet, PC, client-server, LAN.
Large	**Cluster 2:** mainframe computers, minicomputers, 4GL, and large-scale relational databases.	None
Moderate	**Cluster 3:** EIS, CAD/CAM, expert systems, and ISDN.	**Cluster 5:** imaging and CASE.

2) **Cluster 2**: information technologies that slowly diffused among a large proportion of potential adopters. These include mainframe computers, minicomputers, 4GL, and large-scale relational databases.
3) **Cluster 3**: information technologies that slowly diffused among a moderate proportion of potential adopters. These include EIS, CAD/CAM,[8] expert systems, and ISDN.
4) **Cluster 4**: information technologies that quickly diffused among a maximal proportion of potential adopters. These include spreadsheet, PC, client-server, and LAN.
5) **Cluster 5**: information technologies that quickly diffused among a moderate proportion of potential adopters. These include imaging and CASE.

[8]The low saturation levels for this technology should be interpreted with caution since all firms in the sample are not potential adopters. The implications of this for clustering is that CAD/CAM might actually be in cluster 2 rather than cluster 3.

VI. INTERPRETATION AND OBSERVATIONS

Technology innovation in general, and IT innovation in particular, have been studied by researchers for many years. A number of researchers have examined a set of technology innovations attempting to uncover common patterns. These studies, however, were conducted in areas other than IT, such as manufacturing (e.g., [2], [3], [12]) and consumer goods [47]. Based on the diffusion data from a large variety of information technologies and the tentative classification of these ITs as presented above, we may now address the third research objective: to explore the relationships between innovation characteristics of the information technologies and their general diffusion patterns.

Some of the most important contributions to the field of innovation have been the work of researchers like Rogers [45], Rogers and Shoemaker [44], and Rothman [46] on innovation characteristics. As reviewed by Tornatzky and Klein [55], ten innovation characteristics have been examined by researchers:

1) compatibility;
2) relative advantage;
3) complexity;
4) cost;
5) communicability;
6) divisibility;
7) profitability;
8) social approval;
9) trialability;
10) observability.

These characteristics represent interactions between the innovation and its context as perceived by the adopting entity. As discussed by Tornatzky and Klein [55], there is considerable overlap between these characteristics, e.g., between relative advantage and profitability. In general, however, these characteristics have been treated as independent variables in studies that relate them to the dependent variables of innovation: adoption and implementation. In a meta-analysis involving 75 innovation characteristics studies, Tornatzky and Klein [55] reported that the first three characteristics—compatibility, relative advantage, and complexity—have been found to consistently influence innovation adoption and/or implementation in a significant number of published studies.

According to Rogers and Shoemaker [44], the compatibility of an innovation is "the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of the receivers." The definition of relative advantage given by the two researchers is "the degree to which an innovation is perceived as being better than the idea it supercedes," and complexity is "the degree to which an innovation is perceived as relatively difficult to understand and use."

The two major parameters of the diffusion curve: level of saturation and coefficient of imitation, can be related to innovation characteristics. According to Tornatzky and Klein's [55] meta-analysis, the higher the likelihood of adoption, the greater the compatibility, relative advantage, and less complexity of the innovation. Thus, the saturation level, which corresponds to the percentage of potential adopters who actually adopted the IT eventually, should reflect the compatibility, relative advantage, and complexity of the IT over the course of its diffusion. The coefficient of imitation represents the tendency among potential adopters to imitate from those who have already adopted the technology at a given time. While the saturation level represents the final outcome of diffusion resulting from various innovation characteristics, the imitation coefficient represents the dynamic process of diffusion among the society of potential adopters.

A. Relative Advantage and Saturation Level

As suggested by the works of Brynjolfsson and his colleagues [6], [7], which revealed very promising empirical evidence linking productivity gains to the adoption and implementation of ITs in organizations over the years, the eventual saturation level of an IT may be related to its relative advantages. In analyzing patterns of our study results, we first observed that technologies that were adopted by a maximal proportion of potential adopters (Clusters 1 and 4) provided either general support for all members in the organization (spreadsheet, PC, e-mail, fax, and teleconference) or infrastructure that enhanced effectiveness of the organization as a whole (client-server, EDI, and LAN). In the case of EDI, for example, empirical evidence demonstrating benefits for adopters has been established [26], [37]. Facilitated by PCs and software such as spreadsheets and word processors, computing had reached a high level of diffusion and success in organizations toward the end of 80s [35].

In contrast, technologies that reached just a moderate proportion of potential adopters (Clusters 3 and 5) mostly provide specialized support for certain classes of users in the organization, not all members. These include executives (using EIS) and professionals such as engineers (using CAD/CAM), systems analysts (using CASE), and other specialists (expert systems users). As discussed earlier, there is a high level of correlation $(r = 0.727, p < .01)$ between the extent of diffusion (percentage of companies that have eventually adopted an innovation) and infusion (the average penetration of the technology within the companies). This provides tentative empirical support to our observation that the extent that a new IT diffuses among potential adopting organizations, in general matches the extent it appeals to potential users in these organization.

These patterns and empirical findings suggest possibilities for our first observation: *The relative advantage of a new information technology will be a primary determinant of the innovation's eventual level of saturation among potential user organizations, and such advantage may be evaluated by whether the technology has the potential to enhance the efficiency and effectiveness of the organization as a whole, or merely provide specialized support for certain classes of users in the organization*.[9]

B. Compatibility and Complexity and Saturation Level

Available evidence shows that the innovation characteristics of ITs in Clusters 1 and 4 are also consistent with the ideas of high compatibility and low complexity. The relatively low level of complexity with technologies such as spreadsheet, PC, fax, and e-mail is evident due to their ease of use. These technologies are also highly compatible, as they support a variety of computing and communication tasks that need to be performed constantly, and the technology facilitates, rather than al-

[9]Aberrations to this pattern is possible due to emergence of substituting technologies. CASE technology, for example, has been eroded by windows-based rapid prototyping tools. Intranet web technology is now being used in applications, which used to depend on imaging. ISDN did not reach a majority of potential adopters due to high level of uncertainties in technical standards in this area. Now ISDN is making a limited albeit specialized comeback in the Internet access area.

ters these tasks. For example, the client-server technology, unlike the legacy systems before it, can be configured to distribute data and application resources within the organization to closely match the existing decision centralization and decentralization structures of the firm. This flexibility facilitates its compatibility as an innovation [22].

Consider the technologies such as mainframe, mini, large-scale relational database, and 4GL (which runs on mainframes or minis) in Cluster 2. To a large extent, these systems share similar innovation characteristics with those of Cluster 1. The relative advantage is quite high, as these technologies were mainly responsible for the early success of computerization and the resulting tremendous gain in operational efficiency. However, studies have shown that centralized computing is often inconsistent with decentralized organizational structure [27], and the traditional legacy systems are well known for their technical complexity when compared to the point-and-click interface of the Windows environment. These factors, in addition to the high cost, may be responsible for the less than maximal saturation level of these technologies.

Research to date has shown considerable implementation problems for ITs in Cluster 3 and 5 due to a high level of technical complexity and a low level of compatibility of these technologies, which are generally intended for highly trained professionals. The technical complexity of expert systems involving knowledge engineering and knowledge base maintenance, for example, has plagued many expert systems development efforts and contributed to their failures [13]. The compatibility of technologies in this group has also been problematic. For example, CASE technology and its accompanying information engineering (IE) practice had serious problems in user acceptance [38]. In many critical areas, the technology demanded practices like shared data access,which is contrary to existing values in the user community [38].

Conclusions from these previous studies suggests the possibility for our second observation: *there is a general pattern of positive relationship between the compatibility level of an IT and its eventual saturation level, and a negative relationship between extent of complexity and saturation.*

C. Market Externality and the Coefficient of Imitation

As discussed previously, the coefficient of imitation represents the internal influence among adopters of the technology in the society, capturing the dynamics of the process of learning from each other's experience in adopting and implementing the technology. We observed that the relatively slower diffusion of innovations in Cluster 1 could be related to network effects. For technologies such as EDI, fax, teleconference, and e-mail, the perceived relative advantage was severely hampered at the beginning when few organizations were using it and the technology was not considered as useful, as opposed to later, when the user population reached a critical mass [33]. For such technologies, the utility to each user grows as more users join the network of existing users.

This characteristic of the technology, which is commonly termed market externality, is not among the ten innovation characteristics analyzed by Tornatzky and Klein [55]. It can be argued that this is strictly a technial attribute, not an innovation characteristics. However, as our results suggest, market externality has important ramifications for the dynamics of the diffusion process, as manifested by the coefficient of imitation. Thus, we put forth our third observation: *for information technologies having similar potential for adoption by potential user organizations, those that depend on market externality will diffuse more slowly than those that do not have this constraint*.[10]

D. Tool Versus Systems Technology and the Coefficient of Imitation

Certain ITs require intricate development work by technical professionals in its adoption. Successful adoption of expert systems, for example, requires painstaking knowledge engineering and a constantly refreshed knowledge base [13], [56]. In a similar vein, EIS adoption depends on adequate data resources and proper identification of executive information requirements [23], [43]. Technologies requiring such professional development work in their adoption and implementation will be termed systems technologies. In contrast, tool technologies such as PC and spreadsheets require relatively little development work and can be applied to support users' tasks after a brief period of training. This observation may help to explain why Cluster 4 technologies have spread more quickly and have a higher coefficient of imitation than those included in Cluster 1. CASE technology in Cluster 5 is also such a tool that may be used to support systems development tasks, and no extensive front-end development work is needed to make the tool itself work. Similarly, imaging technology is a tool and can be deployed rather quickly (although setting up imaging in a workflow system requires organizational investment). In contrast, systems technologies such as EIS and expert systems in Cluster 3 spread more slowly.

The above analysis and empirical evidence suggest the possibility for our fourth observation: *tool technologies that can be directly utilized as a support tool by users will have lower set-up time and, hence, diffuse faster than systems technologies that require extensive professional development or training in adoption and implementation of the technology*.[11]

E. Further Discussion

It should be stressed that our interpretation of findings and the four observations, although consistent with a substantial body of previous studies, represent preliminary "pattern matching" efforts and must not be construed as scientific conclusions based on empirical data analysis. They are presented only for the purpose of exploring possibilities of further studies to link IT innovation characteristics and its diffusion

[10]We suspect, however, that the slow diffusion will either fail or result in a critical mass that then leads to faster diffusion levels, once the benefits of the technology are established.

[11]It should be noted that there is some degree of overlap between the complexity that restricts saturation levels and the set-up times required for systems technologies that restricts diffusion rates.

TABLE VIII
POTENTIAL RELATIONSHIPS BETWEEN INNOVATION/TECHNOLOGY CHARACTERISTICS AND DIFFUSION PATTERNS

Proportion of adopters (Saturation level)	Speed of diffusion (coefficient of imitation)	
	Low	High
Maximal	**Cluster 1:** • Provide high level organizational wide support for efficiency and effectiveness • High compatibility • Low complexity in use and implementation • Higher market externality requirement • Might require start-up time investment for adoption	**Cluster 4:** • Provide high level organizational wide support for efficiency and effectiveness • High compatibility • Low complexity in use and implementation • Usually lower market externality requirement • Usually limited start-up time investment
Large	**Cluster 2:** Relative advantage quite high, but could involve expense, complexity, that inhibit full adoption. Also might have some externality needs and start-up time.	**Cluster 2***** Relative advantage quite high, but could involve expense, complexity, that inhibit full adoption. Limited externality needs and start-up time
Moderate	**Cluster 3:** • Relatively specialized support for certain classes of users. • Advantages are not certain, extensive or visible due to complexity in implementation or use and/or alternative technological options. • Higher market externality requirement • Might require start-up time investment for adoption	**Cluster 5:** • Relatively specialized support for certain classes of users. • Advantages are not certain, extensive or visible due to complexity in implementation or use and/or alternative technological options. • Usually lower market externality requirement • Usually limited start-up time investment

Note: Cluster 2*** is described despite the fact that none of the technologies in this study fell into this cluster.

patterns. Table VIII summarizes the potential relationships observed above that may provide clues in uncovering such linkages by future researchers. Rigorous validation of these potential relationships through elaborate measurements and formal hypothesis development and testing may lead to reliable methods for predicting patterns of IT innovation adoption and diffusion.

VII. CONCLUSION

In this study, we focus our research effort on three objectives. To accomplish the first objective, four alternative diffusion models were fitted on innovation data for 19 information technologies. From this modeling effort, we sought to identify a robust common representation for the diffusion patterns—the mixed influence model as depicted by the Bass curve. As the external influence parameter was found to be extremely small compared to the internal influence parameter for all the technologies, the results suggest that the diffusion of a new information technology occurs mostly through contacts among society of potential user organizations, and the diffusion is essentially an imitation process. Built upon the common representation, we approach the second research objective by classifying the 19 ITs through cluster analysis based on their eventual saturation level and the coefficient of imitation. To move toward the third research objective, we explored the possibility of matching the cluster patterns with innovation characteristics and tentatively put forth a set of four observations relating innovation characteristics of new information technologies to their diffusion patterns.

The study has made a valuable contribution to both research and practice. In considering the contribution and the generalizability of the study results, however, it is important to exercise caution and recognize that the study is a limited first step in broadening the research agenda on IT innovation. The results were derived from a large set of representative technologies, but there are other technologies that were not included. Also, while the inductive pattern-matching analysis was based on innovation theories and previous empirical findings, the observations require rigorous further work for empirical verification. However, they should be viewed as an important preliminary effort toward the broader objective of searching for plausible relationships between innovation/technology characteristics and its diffusion patterns.

For practitioners, our research findings can be very useful to IS management in an environment where constant innovation is increasingly valued. When a new information technology is being introduced into an organization, a high level of uncertainty and anxiety is usually the norm rather than the exception. From a strategic and competitive standpoint, top IS managers must decide the speed with which to embrace the new technology. As this decision depends on whether we anticipate competitors to quickly adopt and implement the technology, being able to (*a-priori*) estimate the technology's general pattern of diffusion should prove invaluable to top IS managers in this regard. It should also be helpful in planning and scheduling resource commitment during the adoption process within the firm, as our findings also indicate that the internal diffusion of the technology is closely related to the external diffusion pattern of the technology.

For research, this study has helped to move innovation studies in a number of new directions. Previous attempts at modeling IT diffusion were typically focused on a single technology. In this study, we attempt to examine diffusion patterns of a large number of ITs. This provides an opportunity to find a robust common representation for IT innovation diffusion patterns that has not been attempted by researchers. Further contribution is made through the identification of clusters and the tentative association of innovation/technology characteristics to the diffusion patterns.

Previously, diffusion modeling and theories of innovation attributes are separate areas of research, and in this study we made a preliminary attempt to bridge the gap between the two areas. In doing so, we hope to open a new avenue for a more integrated and holistic approach to the study of innovation phenomena. Further research can refine the results of this study to permit more precise calibration of the parameters. This may be attempted by empirically establishing the relationships between the innovation characteristics and the diffusion patterns through a longitudinal study approach. Empirical studies of this genre have been reported for other innovations [31], [32], and similar works on IT innovations hold great promise. For a set of new technologies, perceptions of innovation characteristics such as relative advantage, compatibility, and complexity can be gathered at several points in time throughout the diffusion process. Data on these perceptions can then be associated with the diffusion parameters. Based on these empirically derived associations, we can then attempt to predict diffusion patterns of newer, more contemporary IT innovations.

As the new millennium dawns, the pace of technological change is accelerating, and this is especially evident in the information technology area. An ultimate objective of innovation research is to be able to predict technology diffusion, implementation and effectiveness [48]. By integrating innovation attributes theories and diffusion modeling research, we are taking a modest but significant step toward developing practical approaches for predicting technology diffusion patterns. The preliminary findings from this study should provide a basis for further work to enrich our knowledge of managing innovation in the age of rapid successions of new technologies.

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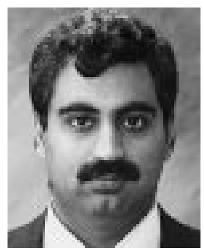

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