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Technology Adoption Life Cycle and Sustainability in ERP Industry - A Data Envelopment Analysis Approach

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ABSTRACT

The Technology Adoption Life Cycle (TALC) has been used in studying the sustainability of hyper-growth, high-tech markets. Recent work in this area has identified the presence of "chasm" in this lifecycle. Since most technology products ultimately derive their value from software, this study explores the effect of chasm on the sustainability issues in software industry. This paper presents an empirical study of selected ERP companies during the period 1989–2004. We investigate whether these companies experience the stages of TALC and the chasm effect as seen in other high-tech markets. Using financial data, we focus on R&D / Marketing expenses and sales revenue of companies and apply DEA to measure efficiency and investigate the sources and level of inefficiencies in these companies. The results demonstrate that efficient companies are not just investing more in R&D and Marketing, but are in fact managing the inputs better than the inefficient companies.

Keywords

Chasm, DEA, ERP, Sustainability, Technology Adoption Life Cycle

INTRODUCTION

The process of innovation, adoption and diffusion of new products has been an area of interest to both academics and practitioners. As observed by Gerrard and Cunningham (2003), Rogers (1995) work has encouraged more than 3800 research studies in the area of diffusion of innovations. However, the innovativeness of IT in terms of products viz. Hardware or Software; their complex nature; the short lifecycle; and high risk in adoption decision (Saaksjarvi 2003)) make them unique as compared to other innovative products or services.

Recently there have been some articles that question the investments in IT and classify IT as a commodity (Carr 2003).But they fail to acknowledge that IT has two components, viz: Hardware and Software. Although the low cost and high availability of hardware may make people think of their use as a commodity, real power of IT lies in software and the use of IT as a process. Since most technology products ultimately derive their value from software, both academicians and practitioners have significant interest in examining new software applications in terms of their adoption and benefits to the organizations.

Practitioners are motivated to develop and enhance software applications that can improve upon the existing business processes or can change the business processes itself. A prime example of such a software system that supports daily business operations and decision making by radically transforming the flow of information across an organization is "Enterprise Resource Planning (ERP) System". There has been lot of studies on the ERP implementation and adoption in the organizations (Moller, Kræmmergaard, Rikhardsson, Moller, Jensen and Due 2004). Most of these studies are from the users' perspective and assess the success and failures of these systems in terms of impact on the organization. However, there are not many studies that have examined the success of ERP applications from the vendors' perspective. In this paper, we systematically study the productivity and business performance of ERP companies using Data Envelopment Analysis (DEA). The research reported in this paper is based upon the work of Rogers (1995) and Moore (1999), and extends prior work in innovation and diffusion of technology.

This paper presents an empirical study of selected ERP companies during the period 1989–2004. We investigate whether these companies experience the stages of Technology Acceptance Life Cycle (TALC) and the chasm effect as seen in other high-tech markets. Using financial data, we focus on R&D / Marketing expenses and sales revenue of companies and apply DEA to measure efficiency and investigate the sources and level of inefficiencies in these companies.

The remainder of the paper is as follow: Section 2 discusses ERP Systems, Technology Acceptance Life Cycle and the Chasm effect faced by the organizations. Section 3 gives an overview of DEA. Section 4 describes the methodological approach. Section 5 discusses Empirical Analysis and Results of the study. Section 6 presents the conclusions followed by limitations and suggestions for further research.

THEORETICAL BACKGROUND

Enterprise Resource Planning (ERP) Systems:

These are applications designed to support and automate the organizational business processes and include modules for manufacturing, distribution and financials, to name a few. They help the organizations to re-engineer their business practices to become agile in responding to customers' needs and face competition in the industry. Yesterday's ERP systems like material requirements planning (MRP) and manufacturing resource planning (MRPII) systems have now grown into Enterprise Systems that include support for a variety of front office and inter-organizational activities like customer relationship management and supply chain management, etc.

As observed by Saaksjarvi (2003), Robertson (1971) classifies innovations into three categories: continuous (slight modifications to existing products), dynamically continuous (creating a new product or modifications to existing ones), and discontinuous.(creation of previously unknown products). Also, Danaher, Hardie, Putsis and William (2001) and Kim, Srivastava and Han (2001) proposed the concept of multigenerational innovations that are newer versions of existing products. Against this backdrop, we surmise that each ERP system supplied by a different company starts as discontinuous innovation and later gets transformed into multigenerational innovation. However, different innovations that enter a market are diffused at different speed (Martinez and Polo 1998). Same is the case with ERP systems. Some applications are accepted very quickly while others remain in the market for a lengthy period of time until they are acquired by a majority. Since most ERP companies derive their major revenue from ERP products, they are uniquely amenable to the analysis of innovation and diffusion

Technology Adoption Life Cycle & Chasm

Rogers (1995) defined innovation as an idea or object perceived to be new in terms of knowledge, persuasion or decision to adopt by an individual, and diffusion as the process of communicating innovation over a time among the members of a social system. For the purpose of this study, we consider ERP systems as an example of an innovation that is diffused at different levels across various organizations.

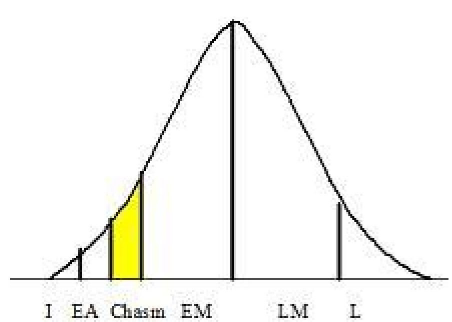

Figure 1

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Rogers (1995) divided customers in five categories on the basis of time taken by them to adopt a new product: innovators (I), early adopters (EA), early majority (EM), late majority (LM), and laggards (L). Moore (1999) extended his work by suggesting the presence of a chasm between EA and EM that represents an observed phenomenon in technology adoption as many technical innovations fail to go past the early adopter stage to the early majority (Figure 1). Gaining early majority definitely help to gain early market success, but fewer number of early adopters makes it difficult for an organization to attain market leadership based on their acceptance of the product. According to Moore (1999), innovators or EA focus more on the concept whereas EM wants assurance of reliable application of the product. This governs the need of adequate R&D activities for the development of the product. Also, EM tends to be absolute observers of activities in the industry. It makes important the need of proper exposure in terms of advertising and communicating the benefits of the product. Thus, in order to overcome the chasm, the marketing and R&D efforts should focus on the factors most salient to the target adoption category.

DATA ENVELOPMENT ANALYSIS (DEA)

DEA (Charnes, Cooper and Rhodes 1978) is a linear programming based technique used to measure the relative efficiency of various units called as Decision Making Units (DMU), where "Efficiency" in general may be defined as ratio of output(s) to input(s). It can help to identify sources and amount of inefficiency of inputs and / or outputs in these DMU's.

DEA has been used in various applications like banking, energy, hospitals, etc to measure the performance of similar units (Banker and Slaughter 1997; Mahmood 1994; Ramanatham 2003). There are many variations of DEA models available in the literature. The "Input Oriented" model aims to minimize the inputs without altering the output whereas "Output Oriented" model aims to maximize the outputs with the same level of input. Some of the widely used DEA models are: CCR, BCC, Multiplicative Model and Additive Model. In this study, we have used CCR and BCC Models, briefly described below:

CCR model (Charnes et al. 1978) assumes that there is no significant relationship between the scale of operations & efficiency, and production is taking place under Constant Return to Scale (CRS). The CRS efficiency, also called as "Technical Efficiency" measures the combined efficiency due to the input/output configuration and the size of operations. BCC Model (Banker, Charnes and Cooper 1984) extended CCR model by allowing for Variable Return to Scale (VRS). According to this model, a rise in inputs results in a disproportionate rise in outputs (Drake and Howcroft 1994). The VRS efficiency score represents Pure Technical Efficiency and measures the efficiency purely due to the input/output configuration. Using the above two scores, Scale Efficiency is calculated as:

$$\text{Scale Efficiency} = \text{VRS Score} / \text{CRS Score}$$

When Scale Efficiency equals 1, DMU is said to be operating at the Most Productive Scale Size (MPSS). Thus, the Technical inefficiencies in a DMU can be either due to ineffective management in converting inputs to outputs (pure technical inefficiency) and / or due to its deviation from the most productive scale size (scale inefficiency). By decomposing Technical Efficiency into Pure Technical Efficiency and Scale Efficiency, we can assess the sources of inefficiencies.

RESEARCH DESIGN / METHODOLOGICAL APPROACH

Model Development:

R&D capability is critical and a reasonable indicator of innovative competences of companies in high-tech industry (Hagedoorn and Cloodt 2003). Customers also feel confident of receiving better product & continued service from companies having superior innovative capabilities (Dutta, Narsimhan and Rajiv 1999). Marketing is also important to identify customer's needs and educate customer about the functionalities and availability of product in order to commercialize the same. Thus, the interaction of marketing and R&D is one of the most important factors of company's performance (Dutta et al. 1999).

To measure the growth and sustainability of ERP software companies, we used their reported revenue as a surrogate measure of market penetration. It has also been used earlier to measure performance of various companies (Chismar and Kriebel 1985; Illueca and Lafuente 2003; Thore 1996). Assuming other operational aspects to be similar, we consider the influences of both marketing and R&D on the performance of the companies. We operationalize them by R&D/Marketing expenses and Sales Revenue reported in the financial statement of the companies.

Although the total sales revenue can be subdivided into different parts (e.g.: License revenue, Service revenue), we feel that the marketing and R&D impact all of them simultaneously. Also, because of high correlation between Total sales, License revenue, and Service revenue for the units in the sample, we use "Total Sales" as a single output for this study.

Choice of DEA Model:

Our model considers each company in a particular year as a distinct DMU that spends in R&D and marketing to achieve sales revenue (Figure 2). Since budgetary allocations for R&D and marketing are controllable factors, whereas Sales revenue is an uncontrollable factor, we decided to asses if the input resources used by the companies can be minimized without changing the output. Against this backdrop, we use "Input oriented model" with both CRS and VRS assumptions in the study. Since ERP companies offer similar set of services with different products, we assume that they are comparable and their difference in performance can be explained by differences in Technical Efficiency. We have used Coelli (1996) to find the solution to the model.

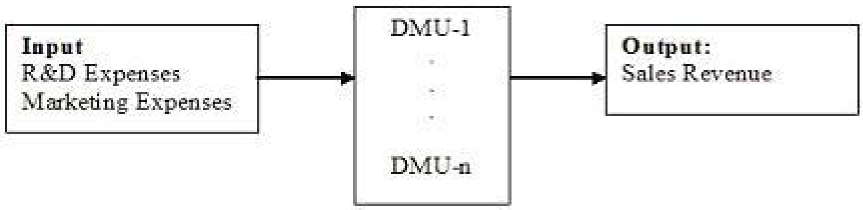


Figure 2

Data Collection

We extracted financial data of some major players in the ERP industry from 1989 through 2004. However, the ERP industrial environment witnessed many acquisitions and mergers during this period. Since the financial data of acquiring company after the merger is reflective of the combined performance of both the companies (acquiring and acquired), we analyze the performance of acquiring company for period after the merger. Using appropriate Price Index, we indexed revenue and expenditure to the year 2004. As shown in Table 1, the descriptive statistics reflects considerable variability in the financial performance of the companies.

Number of DMUs: 205

	Sales Revenue ($)	Marketing Expense ($)	R&D Expense ($)
Mean	1093042	317583	146278
Minimum	1595	701	653
Maximum	11607769	2979690	1278000
Standard Dev	2372705	617559	280911

(Figures in thousands)

Table.1

The study is done in two steps (Figure 3). Firstly, a separate longitudinal analysis is done for each company to assess its efficiency changes and to identify the adoption life cycle stages and chasm effect faced by them. In the second step, we analyze the companies collectively to assess the general trend in the ERP industry and to compare their efficiency relative to each other. We have used both BCC & CRR Models to test for the existence of scale economies.

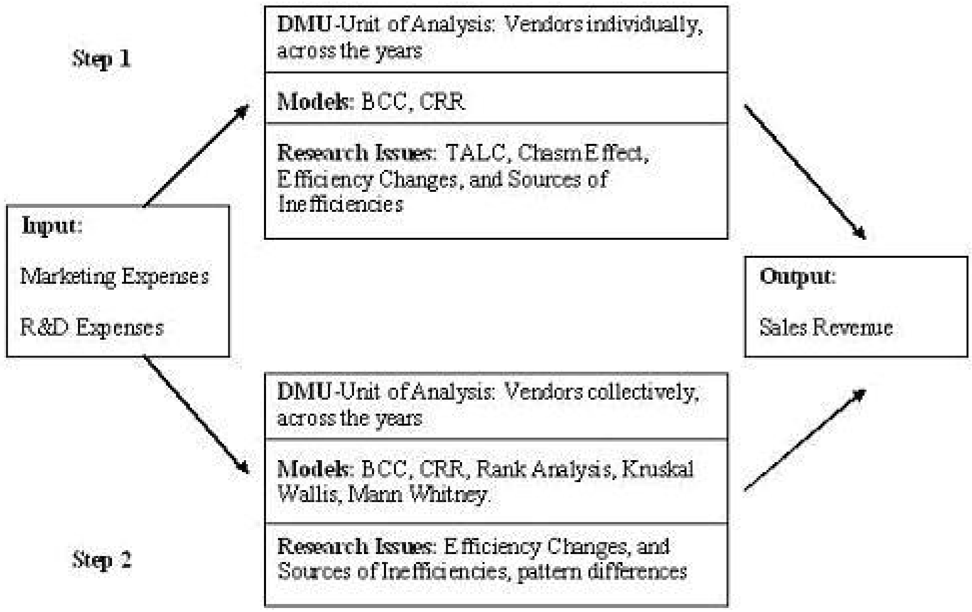


Figure 3 Methodology and Research Issues

ANALYSIS & RESULTS

Step 1: Individual Efficiency Analysis:

Initially, a longitudinal analysis was done to assess Technical Efficiency changes taking place in each company. Using DEA, we identified the best performance year(s) separately for all the companies and evaluated their efficiency in other years relative to these best year(s).

Stages of Product Life Cycle:

In Stages 1 and 2, the companies are in upswing stage and exhibit continued increase in both Marketing and R&D expenses. Thus, the efficiency of the company in this initial stage is low. Since the sales start growing as the innovators and early adopters start buying the system, the efficiency is on the rise till the company faces chasm.

The companies that encounter the chasm will experience a decline in the revenue stream. Also, they'll have to increase marketing expenses to overcome the resistance and reach "early majority". Thus, at this stage the efficiency of the organization will start declining. The company that fails to cross the chasm will continue to experience turbulence in their revenue stream. Once the company overcomes the chasm, it tends to reach the market of early adopters, resulting in increase of sales. The revenue starts increasing steadily and tends to reach the maximum level. Thus, the efficiency of the company starts picking up.

The next target customers are the late majority. Now, the market tends to stabilize and sales level becomes stationary. Thus, though price and margins might have declined, sales /profit are greatest at this stage and the efficiency will remain steady at the maximum value. In the last stage, unless the company extends or diversifies its product line, the sales will fall and the efficiency of company will go down. (Figure 4)

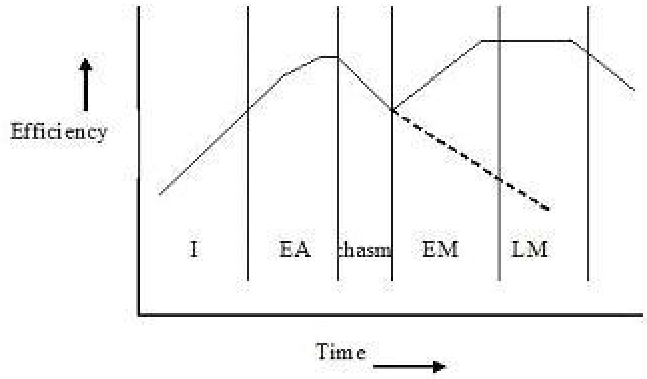
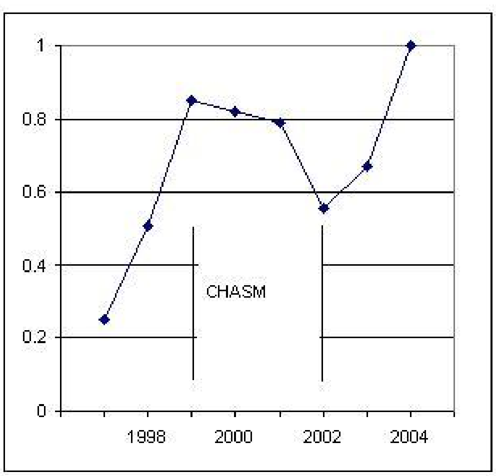
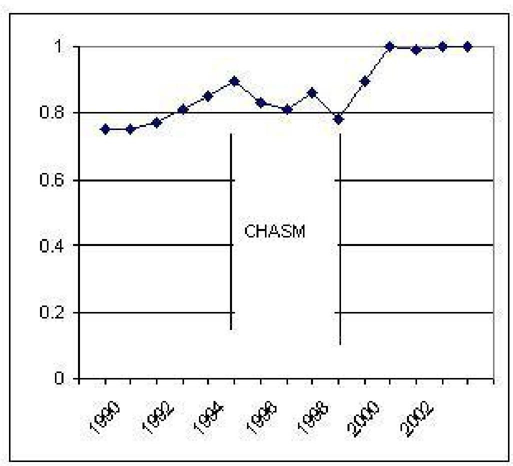


Figure 4

As an example, company A (Figure 5) started with a low Technical Efficiency of 0.25 in 1997 (Stage 1), increasing to 0.82 in 2000 (Stage 2). After 2000, there was a slump in its efficiency and it shows evidence of facing chasm. In 2003, it overcame the chasm and the efficiency again started picking up, signifying its entry into Stage 3. Similarly, company U started with a low Technical Efficiency of 0.75 in 1989 (Stage 1), increasing to 0.89 in 1995 (Stage 2). After 1995, there was a slump in its efficiency and it shows evidence of facing chasm. In 1999, it overcame the chasm and the efficiency again started picking up, signifying its entry into Stage 3. Similar pattern can be seen for other companies. However, as reflected in the above examples, the duration of these stages is not same for all companies as some are able to manage these stages better than the others. Out of 18 companies that we studied, 12 had clear indication of going through chasm, though many were able to overcome while some could not.



Company A



Company U

Figure 5

We observe that most companies have crossed the chasm and are present in Stage 3 of the cycle. This stage is crucial as companies need to capture new markets and enhance the functionalities of products so as to maximize the time to reach Stage 4. In fact, each new innovative product will again live its own cycle from the beginning. Thus, there will be different products in different phases of life cycle, leading to an overall steadiness in the revenue stream of the company.

As the companies move along different stages, we observe a dynamic variation in efficiency through these stages. In general, there is an increase in efficiency at the initial stage, followed by a slump signifying the presence of chasm. The company that fails to cross the chasm faces continuous decline in its efficiency. As the company overcomes the chasm, the efficiency rating again start climbing till it reaches unity signifying the stages of maturity and saturation.

Step 2 (Comparative Efficiency Analysis):

Next, we consider all the companies in different years as separate DMU's and run the model under both CRS & VRS assumptions. We explore how different companies are performing as compared to the most efficient ones in the industry.

	Technical Efficiency	Pure Tech efficiency	Scale efficiency
Min	0.744	0.2083	0.2140
Maximum	1	1	1
Average	0.5540	0.6826	0.8206
Standard Deviation	0.166	0.1938	0.1291
Number of Efficient units	3	20	
Number of Inefficient units	201	184	

Table 2 Descriptive Statistics of Efficiencies

Looking at Table 2, the average Technical Efficiency (0.5540) suggest that on average, inefficient DMU's have potential to reduce R&D and marketing expenses by 44.6% to perform like best practice DMU in the sample. However, since all the inputs are given equal importance, these improvements may not represent the maximum achievable savings in resources. The average Pure Technical Efficiency (0.6826) and Scale Efficiency (0.8206) suggest that, compared to the best practice, companies can achieve the same level of sales with a 31.76% reduction in R&D and market expenses and a further 17.94% reduction by suitably altering their scale of operation. However, the relative sizes of two efficiencies suggest that inefficiency in ERP industry is largely because of inefficient management of resources than of operating at a wrong scale.

As an example, company A has Technical Efficiency of 0.34 in 2004 compared to the best performing unit in the industry for the entire duration. Thus, it needs an overall reduction of 66% in its input to perform like the best in the industry. Its Pure-Technical Efficiency score of 0.43 and Scale Efficiency score of 0.8 suggest that it has a potential to reduce its input by 57% by proper management of resources and another 20% by operating at the correct scale respectively.

Similarly for company R, its low Pure Technical Efficiency (0.76) and relatively high Scale Efficiency (0.94) in 2003 signify that its technical inefficiency (0.71) is mainly due to inefficient management of R&D/marketing expenses compared to the best in the industry. However in 2004, it shows an improvement in its Pure Technical Efficiency (0.91) and Scale Efficiency (0.98), and thus improving its Technical Efficiency (0.89) by proper management and operating at a better scale.

Company Rankings:

We used Kruskal-Wallis test to assess if the companies have identical efficiency ratings. The Kruskal-Wallis Test Statistic = 95.135 > critical value (p=0.0000, 18d.f) clearly rejects the null hypothesis that all companies have identical efficiency ratings. Thus we conclude that there are at least some companies which tend to attain higher efficiency ratings than others. This result allowed us to proceed further by dividing the companies into two groups (Efficient and Inefficient) and assess the difference in their performances.

Following Thore (2002), we ranked all DMU's in ascending order, giving rank 1 to DMU with lowest efficiency score. In order to break ties for the fully efficient companies (efficiency=1), we use the measure of super efficiency (Anderson and Peterson 1993) that examines the maximal radial change in inputs and / or outputs possible for a DMU to remain efficient. The larger this value, the higher is DMU positioned amongst the efficient units. Next, we calculate the average ranked score of each company. The higher the average ranks, the higher the ranked position and more efficient is the company (Table 3).

	A	B	C	D	E	F	G	H	J	K	L	M	N	P	Q	R	S	T	U
1989					25							204			66				13
1990			114		32				181		172	76			45				21
1991			124	16	51				154	49	197	40			74				42
1992		199	146	22	87				145	69	166	54			101				62
1993		167	118	135	107	180	200		133	47	164	64			100			78	68
1994		202	136	39	110	73	201		115	67	170	116	53		46			52	89
1995		187	139	34	91	41	149		81	71	192	112	33		43			23	63
1996		175	151	19	96	37	162		109	122	185	117	10	182	48			12	59
1997	9	156	153	14	104	50	198		123	111	178	140	35	11	84			30	65
1998	1	61	157	80		56	190		79	141	177	150	58	186	119			72	57
1999	6	105	148	55		60	165	106	88	152	193	120	17	203	126		174	38	95
2000	3		144	28		75	179	94	93	98	191	143	108	8	121		158	85	129
2001	5		86			18	168	137	24	70	205	159	99	176	160		173	90	125
2002	2		29			161	171	127	27	82	189	142	113	147	20	7	184	163	130
2003	4		44			188	155	103	36	92	183	134	83	97	77	138	195	194	128
2004	15		26					131	31	102	196		132			169			
Average rank	**5.63**	**156.50**	**114.33**	**44.20**	**78.11**	**85.36**	**176.18**	**116.33**	**94.60**	**90.93**	**183.87**	**118.07**	**67.36**	**126.25**	**82.00**	**104.67**	**176.80**	**76.09**	**76.40**
Ranked Position	**1**	**16**	**12**	**2**	**6**	**8**	**17**	**13**	**10**	**9**	**19**	**14**	**3**	**15**	**7**	**11**	**18**	**4**	**5**
Group	**Rated-Ineffl**	**Rated-Effic**		**Rated-Ineffl**	**Rated-Ineffl**		**Rated-Effic**				**Rated-Effic**	**Rated-Effic**	**Rated-Ineffl**	**Rated-Effic**			**Rated-Effic**	**Rated-Ineffl**	**Rated-Ineffl**

Table 3

Dividing the ranked companies into three parts, we group the top 1/3 as "Rated-Efficient" and bottom 1/3 as "Rated-Inefficient" group to test for the differences in efficiency scores and sources of inefficiencies between them. Descriptive statistics in Table 4 shows the difference in performance of these two groups. On an average, Rated-Efficient group spend more on R&D and Marketing than Rated-Inefficient group.

		Min	Max	Average	St Dev
Rated-Efficient	**Sales Rev.**	2636	2431204	11607770	3535663
(L,S,G,B,P,M)	**Marketing Exp**	701	2979690	658405.1	907386.6
	R&D Exp	653	1278000	293469.6	408489.9
	Technical eff.	0.28	1	0.6546774	0.1689042
	Pure Tech eff	0.343	1	0.8557742	0.1635014
	Scale effic	0.308	1	0.767258	0.1304973
Rated-Inefficient	**Sales Rev.**	1595	1220430	246372.2	347355.5
(E,U,T,N,D,A)	**Marketing Exp**	2023	631192	101316.6	154014.6
	R&D Exp	1836	198682	40021.92	52294.62
	Technical eff.	0.074	0.924	0.46275	0.1429833
	Pure Tech eff	0.208	1	0.5452968	0.1552883
	Scale effic	0.214	0.998	0.8500625	0.131756

Table 4

Before assessing the differences in the sources of inefficiencies, in order to validate if these groups are statistically significantly different in terms of their overall combined efficiency due to their managerial practices regarding input/output configuration and the size of operations, we test for the following hypothesis:

H1: Rated-Efficient Group have high Technical Efficiency than Rated-Inefficient Group.

If the companies do not manage their resources properly, and / or do not work at an optimum scale of operation, they will not achieve the desired level of output. It implies that "Rated-Efficient group must be following better management practices and performing close to the MPSS as compared to other group. Thus, we test for the following hypothesis:

H2: Rated-Efficient Group will have high Pure Technical Efficiency than Rated-Inefficient Group.

H3: Rated-Efficient Group will have high Scale Efficiency than Rated-Inefficient Group.

(Efficient-Inefficient)				
		Z	p value	Decision (a = .05)
H1>0	Technical Efficiency	6.2073	0.00	Reject Ho
H2>0	PureTechnical Efficiency	7.8604	0.00	Reject Ho
H3>0	Scale Efficiency	-4.3068	0.00	Accept Ho
H4>0	R&D Expenses	2.9108	0.00	Reject Ho
H5>0	Marketing Expenses	2.4814	0.00	Reject Ho

Table 5

Using non-parametric Mann Whitney test, we found support for H1, validating our division of companies into two groups based on the efficiencies. The test also supported H2 that "Rated-Efficient" companies have higher Pure Technical Efficiency than "Rated-Inefficient" companies" (Table 5). Thus, we conclude that inefficient group was not managing their resources as effectively as the efficient group.

However, H3 was rejected (Table 5), and in terms of Scale Efficiency, the inefficient companies were supported to perform better. One reason could be that in general, efficient companies tend to be well established large companies with multiple products and have more resources to invest in marketing and R&D. About the inefficient companies, these were found to be new companies with restrictive amount of funding for their operations. Thus, this group tends to operate close to the MPSS

Finally, we also assess the differences in Marketing and R&D expenses (H4 and H5) for the two groups and found support that Rated-Efficient groups outperformed the Rated-Inefficient group in both Marketing and R&D expenses (Table 7). It also justified that Rated-Efficient groups are investing more in R&D and marketing, as mentioned above.

CONCLUSION

This paper contributes to the limited number of empirical studies that attempt to empirically assess the life cycle of Software products. In this study, we analyze the trends in the productive performance of ERP companies across the time and our results validated the presence of the chasm in this lifecycle which has a significant impact on the sustainability of market share. By investigating a particular software system (ERP), we hope to control for various risks and market conditions.

These findings have important implications for both academics and practitioners. The results demonstrated that there is an increase in efficiency at the initial stage, followed by a slump in efficiency signifying the presence of chasm. Then again there is an increase in efficiency for the companies that are able to overcome the chasm, followed by stabilized growth path and finally a decline in efficiency, signifying the stages of maturity and saturation. Thus, it empirically validates the Technology Adoption Life Cycle and presence of chasm in the ERP industry.

The study found that the overall efficiency of the companies due to their input/output configuration and scale of operation was low in the beginning stages. It later increased till the companies faced chasm. However, the companies that suitably altered their resource usage by changes in the managerial practices and by choosing an appropriate scale of operation were able to successfully overcome the chasm and see an increase in their efficiency.

The study also found that though the impact of inefficiency due to operating at a wrong scale of operation was less compared to inefficient management, the organizations in general were not operating at the most productive scale size. The results also demonstrated that efficient companies are not just investing more in R&D and Marketing, but are in fact managing the inputs better than the inefficient companies. The findings in this study suggest the ERP companies to look into their mode of operation and take an appropriate decision concerning their way of resource management and / or scale of operation. It is thus expected that the study will give an insight to the ERP companies about their performance and sources of inefficiencies. To the organizational users (customers) of the ERP system, the methodology can help to establish an objective measure to compare the performance of various ERP companies before investing their resources.

LIMITATIONS & FURTHER RESEARCH

This research is based on the secondary financial data using non-random sample of ERP companies that may have an impact on the generalizability of results. Also, there may be other factors (cultural or behavioral) specific to different companies that have an impact on the company's performance. But these factors are not considered in this study. Common to all studies using DEA, it may be possible for a unit outside the sample to achieve a higher efficiency than the best practice DMU in the sample. These issues need to be considered before utilizing any conclusion from this study.

Though this research addresses the ERP software, it would be interesting to assess its generalizability by testing it with other software products due to difference in their inherent characteristics. Also, future studies can expand the results reported here by using techniques like "Window Analysis" and "Malmquist Index models" that are useful to measure productivity changes through time.

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