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Ashish Sood and Gerard J. Tellis

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The S-Curve of Technological Evolution: Strategic Law or Self-Fulfilling Prophecy?

Ashish Sood and Gerard J. Tellis

When should a manager shift resources from a current to a new technology? Sood and Tellis examine product performance data for 23 technologies, and find that prevailing beliefs about technological evolution are too simplistic. Their study cautions managers against abandoning mature technologies that still hold promise.

Report Summary

The technology management literature suggests that the performance of a new technology starts below that of an existing technology, crosses the performance of the older technology once, and ends up at a higher plateau, so tracing a single S-shaped curve. Despite limited empirical support for this thesis, the "S-curve of technological evolution" is widely cited to determine at what point managers should shift investments from a mature technology to a new one.

In this study, Sood and Tellis test this thesis. They collect and compare technical data on product performance for 23 technologies across six markets (external lighting, data transfer, computer memory, desktop printers, display monitors, and analgesics).

Their findings refute prevailing beliefs: Most technologies do not demonstrate a single S-shape performance curve. Technologies evolve through an irregular step function with long periods of no growth in performance interspersed with performance jumps. A jump in performance appears to be largest after a long plateau of no improvement.

They also find that new technologies may enter the market *above or below* the performance of existing technologies, and that the performance curves of a pair of competing technologies rarely have a single crossing.

Across the markets and categories they studied, the path of technological evolution was partially predictable. Past improvement in performance of the same technology, improvement or crossing by a rival technology, and especially crossing by a rival technology tended to signal immediate improvement in performance.

In addition, while a new technology competed with the old ones on a primary dimension (an attribute of most importance to customers), the new technology also introduced a sequence of random secondary dimensions which then offered a new basis of competition.

Overall, these results suggest that the prevailing wisdom regarding technological evolution might lead managers to prematurely abandon a mature technology. Managers would be better-advised to vigilantly study the internal dynamics of their technology when making investment decisions. ■

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Introduction

Understanding technological innovation is vital for marketers for several reasons. First, technological change is perhaps the most powerful engine of growth. It fuels the growth of new brands (e.g., Gillette's Mach III), enabling corporations to grow and incumbents to defend established positions. Second, technological change creates new growth markets (e.g., digital video recorders) through radical innovations (Tushman and Anderson 1986). Third, technological change often transforms small outsiders (e.g., Intel) into market leaders replacing leading firms (Foster 1986; Christensen 1997; Chandy and Tellis 1998).

To date the topic of technological evolution has been studied primarily in the technology management literature. A central premise is that performance of a new technology starts below that of an existing technology, crosses the performance of the older technology once, and ends up at a higher plateau, so tracing a single S-shaped curve (see Figure 1a). There is scattered empirical support for the premise and limited theoretical support for various aspects of the S-shape curve (e.g., Foster 1986; Utterback 1994a; Christensen 1997). Belief in this premise is so strong that it has almost become a law in the strategy literature from which authors have derived strong managerial implications. For example, they have warned that even though managers might be able to squeeze out improvement in performance from a mature technology at the top of its S-curve, improvement is typically costly, short lived, and small. Thus, a primary recommendation in the strategy literature and the trade press is that managers abandon a maturing technology and embrace a new one in order to stay competitive (e.g., Foster 1986; Christensen 1997).

A central practical problem that faces managers is when to shift investments from the current to the future technology. If the S-curve is indeed valid, then the appropriate time would be the inflection point of the S-curve. After this point, performance improves at a decreasing rate until maturity.

New product development and major investments in research depend upon a correct understanding of technological evolution in general and of the S-shaped curve in particular. To foster this understanding, this study seeks answers to the following questions:

- How do new technologies evolve? Do they follow the S-shaped curve or some other pattern? Are technological changes predictable? Is the rate of technological change increasing?
- How do rival technologies compete? What are the performance dimensions of competition? What are the transitions between technological changes?
- Which firms carry out and survive technological evolution? Who introduces radical innovations? Do incumbents survive the change?

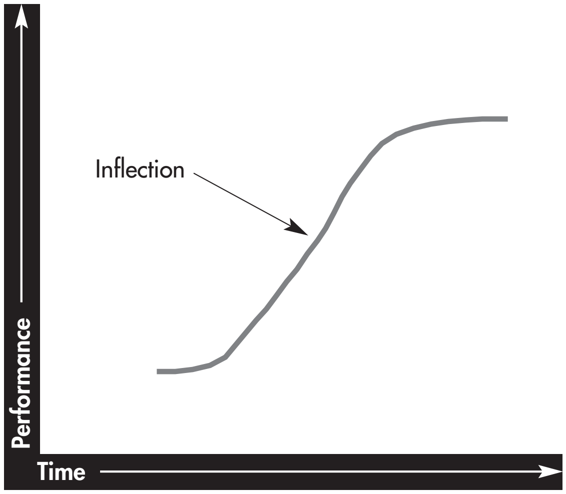
The primary focus of the current study is empirical. We test hypotheses derived from prevailing theory and prior findings, and examine the evolution of 23 technologies in six markets or industries. In the next three sections we present the prevailing theory, method, and results. The last section discusses the findings, limitations, and implications of the research.

Prevailing Theory

The field does not enjoy a single, strong, and unified theory of technological evolution. To guide our empirical work, we reviewed available theory and derived testable hypotheses about the path, shape, source, and speed of technological evolution and the competition among rival technologies.

Theory in this area has been partly confounded by the use of circular definitions. So we begin by defining types of technological innovations independently of their effects.

Figure 1a
Technological S-Curve



Definitions

Beginning with an early study by Schumpeter (1939), researchers have used a wide variety of terms to describe innovations. Many terms such as revolutionary, disruptive, discontinuous, or breakthrough (Freeman 1974; Tushman and Anderson 1986; Garcia and Calantone 2002) are intrinsically problematic because they define an innovation in terms of its effects rather than its attributes. If the definitions are then used to predict market outcomes (e.g., new entrants displacing incumbents from disruptive technologies), researchers run the risk of asserting premises that are true by definition. To avoid such circularity, we define technological change in terms of intrinsic characteristics of the technology. As such, we identify and define three types of technological change: platform, component, and design.

We define a *platform innovation* as the emergence of an entirely new technology based on scientific principles distinctly different from those of the existing technologies. For example the compact disk (CD) used a new platform, laser optics, to write and read data where the prior technology used magnetism.

We define a *component innovation* as one that uses new parts or materials within the same technological platform. For example, magnetic tape, floppy disk, and zip disk differ by use of components or materials although all are based on the platform of magnetic recording.

We define a *design innovation* as a reconfiguration of the linkages and layout of components within the same technological platform. For example, floppy disks decreased from 14 to 8 inches in 1978, to 5.25 inches in 1980, to 3.5 inches in 1985, and to 2.5 inches in 1989, although each was based on the platform of magnetic recording (Christensen 1993).

These definitions may be considered refinements of the technological dimension of radical innovations as defined by Chandy and Tellis (2000).

In our study we use the term new technology synonymously with new platform. Further, we note that platform innovation results in improved performance due to component or design innovations. In the interests of parsimony, this study does not explicitly identify the component and design innovations that improve performance in new platforms.

Theoretical background

In the technology literature, a strong consensus has developed about the phenomenon of technology evolution; a consensus is emerging about the major explanation or theory for this phenomenon.

Regarding the phenomenon, prior research suggests that technologies evolve through an initial period of slow growth, followed by one of fast growth culminating in a plateau. When plotted against time, the performance resembles an S-curve (see Figure 1a). Support for this phenomenon comes primarily from the work of Foster (1986), Sahal (1981), and Utterback (1994a). These authors address the progress of a technology on some primary dimension that is most critical to consumers at the time the innovation emerges. Examples are brightness in lighting, resolution in monitors and printers, and recording density in desktop memory products.

Subsequent authors have either accepted the above view or found additional support for it.

Authors have not developed any single, strong, and unified theory for the S-curve. However, an emerging, and probably the most compelling, explanation revolves around the dynamics of firms and researchers as the technology evolves. We call this explanation the technology life cycle theory because it explains the occurrences of the three major stages of the S-curve of technological evolution: introduction, growth, and maturity (see Abernathy and Utterback 1978 and Utterback 1994a). We describe these stages as emerging from interplay of firms and researchers over the life of the technology.

Introduction Stage. A new technological platform makes slow progress in performance during the early phase of its product life cycle. Two reasons may account for this. First, the technology is not well known and may not attract the attention of researchers. Second, certain basic but important bottlenecks need to be overcome before any new technological platform can be translated into practical and meaningful improvements in product performance. For example, the laser beam was a new platform that required much time and effort to achieve the safety and miniaturization required for a surgical tool.

Growth Stage. With continued research, the technological platform crosses a threshold after which it makes rapid progress. This stage usually begins with the emergence of a dominant standard around which product characteristics and consumer preferences coalesce (Utterback 1974). That consensus prompts focused research on the new platform and rapid increases in its performance. Further, publicity of the standardization draws a large number of researchers to study the new platform. Their cumulative and interactive efforts also lead to rapid increase in performance. Finally, the rapid progress leads to increase in sales of products based on the new technology which leads to increase in revenues and profits and greater support for research. These added resources fuel further improvement in performance (Klepper 1996).

Maturity Stage. After the period of rapid improvement in performance, the new technology reaches a period of maturity when progress occurs very slowly or reaches a ceiling (see Foster 1986; Brown 1992; Utterback 1994b; Chandy and Tellis 2000). Authors have put forth several reasons for this change. Foster suggests that maturation may be an innate feature of each platform—a technology is good for only so much improvement in performance. Utterback (1994b) and Adner and Levinthal (2001) suggest that as the markets saturate, the focus of innovation shifts from product to process innovation. As such, performance increases are few and modest. Reinganum (1985) and Ghemawat (1991) suggest that maturity occurs when there is less incentive for incumbent firms to innovate due to fears of obsolescence or cannibalization from a rival platform. Thus the rate of innovation reduces relative to the growth stage. Perhaps the best explanation is by Sahal (1981). He proposes that the rate of improvement in performance of a given technology declines because of limits of scale (things either get impossibly large or small) or system complexity (things get too complex to work flawlessly). Once these limits are reached, the only possible way to maintain the pace of progress is through radical system redefinition—that is, move to a new technological platform.

Hypotheses

Based on the above theory, we derive hypotheses about six aspects of technological evolution: shape, path, and dynamics of technological change on a primary dimension, progress on secondary dimensions, and the source of innovations and pace of technological transition.

Shape of technological progress

The theoretical background above suggests that technological evolution on a particular performance measure follows an S-shaped curve. However, as also indicated above, research in this area is relatively new and sparse. Extant theory does not indicate the slope of this S-curve, the duration of the early or growth period, or the timing or steepness of the turning points. We will try to determine if one can identify any patterns or generalizations about these parameters. However, in terms of a testable hypothesis regarding shape, the most precise hypothesis we can formulate is:

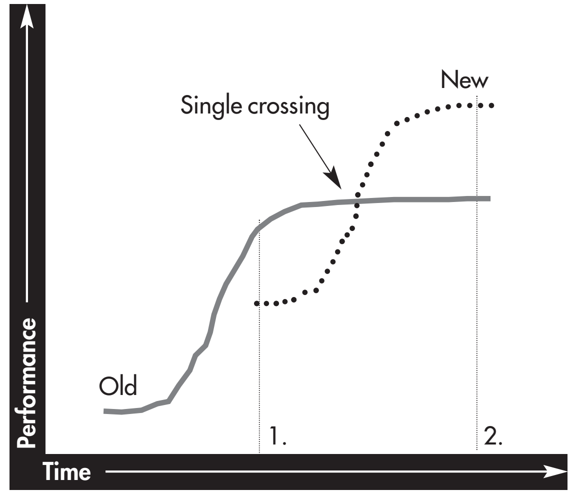
H1: Technological progress on a primary dimension follows a single S-shaped growth curve.

Technological transition and performance of competing technologies

Do the paths of two technologies ever cross? If so, how many times? A crossing signals whether a new technology is robust and productive enough to supplant the old one. The extant literature suggests that such paths do cross and they do so only once. This conclusion in the literature is based on three implicit premises. First, successive technologies each follow an S-curve. Second, the new technology starts its performance below the old technology. Third, the new technology ends above the performance of the old technology.

Support for the first premise follows from that for H1. Support for the second premise comes from several authors. Utterback (1994a) asserts that at the time an invading technology first appears, the established technology generally offers better performance or cost than does the challenger, which still has major problems. Foster (1986) says, "During the fast growth phase of the first technology, the performance of alternative technologies rarely surpasses that of established technologies." Adner and Levinthal (2001) also confirm that "it is unlikely that a new technology will initially dominate an established technology in its primary domain of application." Likewise, Christensen (1992a,b) and Anderson and Tushman (1990, 1991) support the general phenomenon that any new technology provides much lower benefits than the old technology at the time it appears.

Figure 1b
Theory of S-Curves



Similarly, several authors provide arguments and examples in support of the third premise. Utterback (1994a, p.160) states that "the new technology often has so much more potential for better performance that it" ultimately "surpasses the old." Two common examples cited in support of these arguments are steam ships replacing wind-powered ships (Foster 1986) and turbo jet engines replacing internal combustion engines for airplanes (Constant 1980).

Based on the above premises, Foster (1986) and Christensen (1997, p. 398) postulate the following chain of events in the evolution of competing technologies. Sometime in the life of an old technology, a new technology emerges. Initially, it also makes slow progress on the primary dimension. However, at some time, it enters its growth phase and improves rapidly. In contrast, the old technology improves at a much slower rate even though major commitments are made to develop products using old technology. As a result, a point is reached when the new technology crosses the old technology in performance (see Figure 1b). This crossing of the old technology is a signal of the end of its efficient progress. Hence the threat to the old technology on the primary dimension is always from below. This pattern of inter-technology competition results in overlapping S-curves, with each new S-curve starting below but ending above the old. In support of this rationale regarding the relative performance of technologies, some prior studies show a single crossing between any two technologies (Christensen 1997; Foster 1986). This line of argument suggests that:

H2: (a) At the introduction of a new technology, its performance is lower than that of the old technology. (b) At the maturity of a new technology, its performance is higher than that of the old technology. (c) As a result, the performance path of a pair of successive technologies intersects once, when the new technology crosses the old technology in performance.

Dimensions of technological competition

Past research suggests certain secondary dimensions become important as technology evolves. Progress occurs systematically along the first dimension, then moves to the second, then to the third, and so on. These dimensions form the bases of inter-technological competition. They also form the bases by which consumers choose among rival technologies or products. In particular, Christensen (1999) posits that while the new technologies under-perform along traditional dimensions, they are better than old technologies on some secondary dimension.

The literature also suggests that the basis for such competition is quite standard and occurs in the same form across markets. For example, Christensen (1999) points out four generic dimensions of inter-technological competition: functionality, reliability, convenience, and cost. Product functionality is the primary attribute on which consumers choose products in that category. Similarly, Moore (1991) suggests that products start competing on higher reliability after subsequent innovations increase functionality beyond a certain point. Reliability is the product's consistent performance over time. Christensen suggests that after product functionality and reliability requirements are satisfied, firms become more willing to customize product designs to meet customers' specific requirements, such as convenience. Abernathy and Clark (1985) propose that the product becomes a commodity and progress occurs through price reductions once the technology has progressed up the S-curve sufficiently on functionality, reliability, and convenience. The occurrence of such generic dimensions can be important in guiding firms about the path of evolution and the direction of the next competitive attack. This line of reasoning suggests that:

H3: Technological evolution progresses through four generic dimensions of performance: functionality, reliability, convenience, and price.

Pace of technological transition

By pace of technological change we refer to the rate at which innovations are introduced in the market. The pace of technological change may be essentially stochastic in nature, due to the uncertainties in both the frequency of improvements and the magnitude of gain realized through each innovation.

However, some authors believe that innovations are occurring faster, for three reasons. First, every year greater resources are being devoted to research and development. Second, every year an increasing number of countries and peoples get involved in this research and development. Third, the progress in one area (e.g., computers) enables greater efficiencies in another area (e.g., materials design).

At least two studies have found empirical support for this thesis. For example, Qualls, Olshavsky, and Michaels (1981) found that the percentage of products in the introductory and growth phases of the product life cycle was increasing in the last 50 years. This finding suggests that the pace of technological transition is increasing and new products are being introduced at a faster pace. Similarly, Tellis and Golder (1996) find that the time to takeoff of new products is shorter now than in earlier decades. This finding would imply that the rate of innovation is higher now than in earlier decades. Kayal (1999) found an increasing recency in the median age of the patents cited on the front page of a patent document, in the past 25 years. This finding suggests that the cited patents are relatively recent and that the technology is experiencing a frequent replacement of one generation of inventions by another, which is a sign of a rapidly progressing technology. On the other hand, Bayus (1994, 1998) believes that even though more products and product variations are available in the market at any point in time, the rate of change now is not higher than in earlier decades. Hence, we can propose the following null and alternative hypotheses:

H4o: The pace of technological change is constant with calendar time.
H4a: The pace of technological transition is increasing with calendar time.

Source of new technologies

Which types of firms are more likely to introduce the platform innovations: incumbents or new entrants, large firms or small firms? This topic has been the subject of research for decades. The conventional wisdom and dominant view is that platform innovations come primarily from small firms or new entrants. These firms are ridiculed and ignored by incumbents in the beginning, but later grow to be successful with the progress of the new technology. Scherer (1984) shows how new entrants contribute to a "disproportionately high share" of revolutionary industrial products.

Previous studies have also proposed many reasons for large incumbents failing to introduce innovations, including incumbent's technological inertia (Ghemawat 1991), complacency (Robertson, Eliashberg, and Rymon 1995), arrogance (Lieberman and Montgomery 1988), and unwillingness to cannibalize their current products (Chandy and Tellis 1998). Thus the dominant view in the literature is that:

H5: Platform innovations are introduced primarily by small entrants.

Method

A readymade database does not exist for the study of technological evolution. We collected our own data using the historical method, following a growing trend in marketing (see Golder and Tellis 1993; Golder 2000; Chandy and Tellis 2000). The benefits of using the historical method include freedom from survival and self-report bias, ability to assess causality through longitudinal analysis, and new insights from a fresh look at history (Golder 2000). Below we detail our sample selection, sources, and procedure for data collection.

Sample selection

We used two criteria in selecting categories: some overlap with past research and adequate number of platform innovations. We selected a portfolio of categories such that it included some that had been investigated in past studies (e.g., memory and lighting) and others that had not been researched. This coverage allows us to compare our results with past studies and validate these findings in new categories. However, the present study goes further than previous studies in one important aspect—within each category we selected all technologies. We also required that the category must have had at least two platform innovations.

On the basis of these criteria we chose external lighting, data transfer, computer memory, desktop printers, display monitors, and analgesics. Note that the first two are utilities, the next three are consumer electronics, and the last one is medical. Thus the sample crosses a broad spectrum of products.

Sources

The information required for this study is technical data on product performance for various technologies at different stages of its evolution. The primary sources of our data were reports in technical journals, industry publications, white papers published by R&D organizations, and annual reports of industry associations. We sourced industry reports of market research firms (like Disk/Trend or Stanford Resources), press releases, timelines of major firms, and records in museums which profiled innovations and the development of industries. We recorded the current performance of many technologies from product information bulletins released by firms. We used Medline and Cochrane Database of Systematic Reviews for information on the biomedical literature for the analgesics category.

Procedure

We followed the rules for data collection for the historical method (Golder 2000). Despite these efforts, it was difficult to avoid some problems. We explain these problems and the rules we used to resolve them.

First, in some cases, we found conflicting levels of performance between multiple sources for the same technology in the same period. In these cases, we used two checks to record the appropriate performance level for each year. One, we checked to make sure the recorded performance was of comparative models. For example, lamps based on the same technology provide different levels of efficiency depending on the wattage of the lamp; so we ensured that the recorded efficiency was for lamps of the same wattage. Two, if two sources provided conflicting data for a period within the series, we chose the one whose starting and ending values were more consistent with the rest of the series.

Second, within a platform innovation, we found that technologies evolved with component and design innovations. At any particular time, a platform technology could be represented by alternate components and designs. In such cases, we use the performance of the best component or design or combination of the two, as the performance of that platform. For example, magnetic memory is available in various designs—floppies, zip disk, tape, hard disc, etc. Among these, the hard disk had the highest memory. So, we chose the memory of the hard disk as the level of storage capacity of magnetic memory.

We collected intensive data on two entities in each category—the platform technology and the firm that introduced it. In each category, we first identified all the platform innovations. Then we recorded the maximum performance of products in each platform technology for each year from its year of introduction until 2001. None of the past studies makes an explicit statement of the starting point of the S-curve. We use the date of first commercialization of a product based on each technology as the standard starting point to compare the relative performance of any two technologies. We also collected additional information regarding the incumbency status and relative size of the firm at the time of introduction of the technology.

The literature is quite consistent in recommending the use of performance as the key dependent variable when testing the S-curves. For example, Christensen (1999, p. 19) suggests, "A simple graph plotting product performance as it is defined in the mainstream markets on Y axis and time on the horizontal axis." Similarly Foster (1986, p. 274) suggests that we "collect the data on how well the product performed." Utterback (1994a) also identifies the dependent variables as performance when comparing two technologies: "The established technology generally offers better performance or cost than does the challenger, which is still unperfected" (p. 158).

Results

We first present the identification of platform innovations and the performance attributes in each category. Next, we present findings on the hypotheses regarding the shape, path, and dynamics of technological changes. We then present findings on the competition, rate of improvement, and source of new technologies. We used nonlinear regression to test the first and primary hypothesis, the existence of the S-curve. We used cross tabs, chi-square and binomial tests, and regression analysis for the other hypotheses. We used Tobit analysis to

Figure 2a
External Lighting

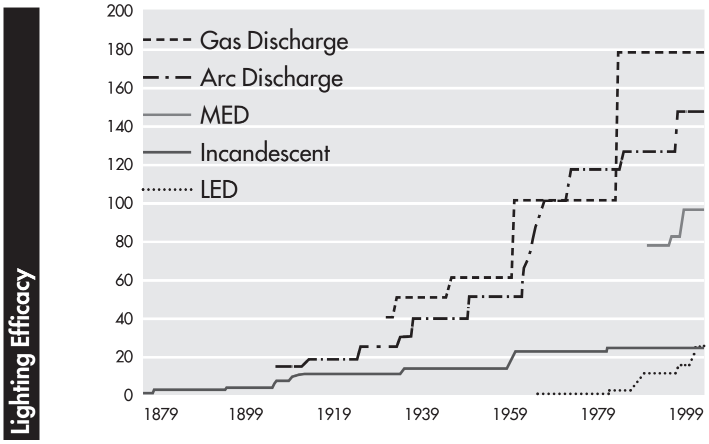


Figure 2b
Desktop Memory*

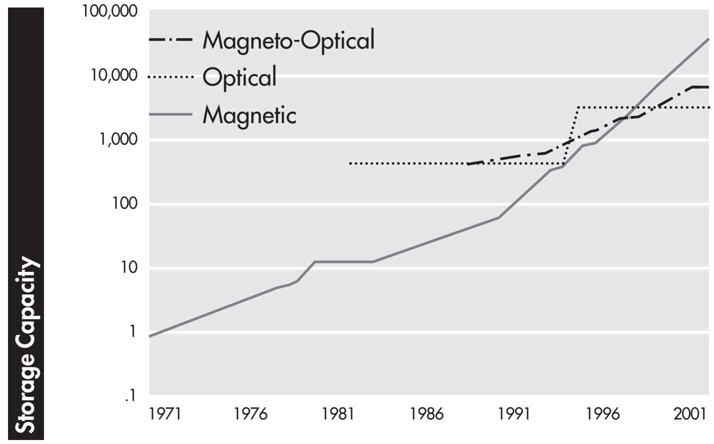


Figure 2c
Display Monitors*

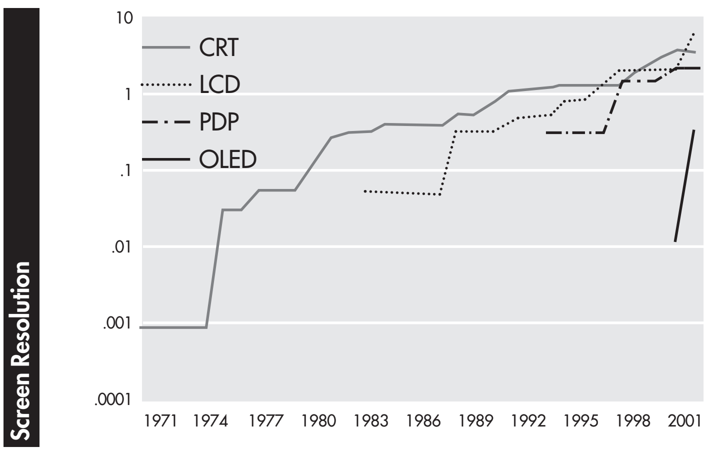


Figure 2d
Desktop Printers*

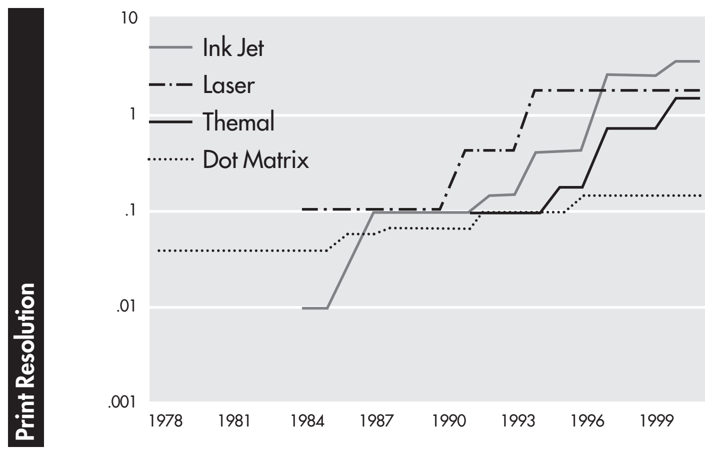


Figure 2e
Data Transfer*

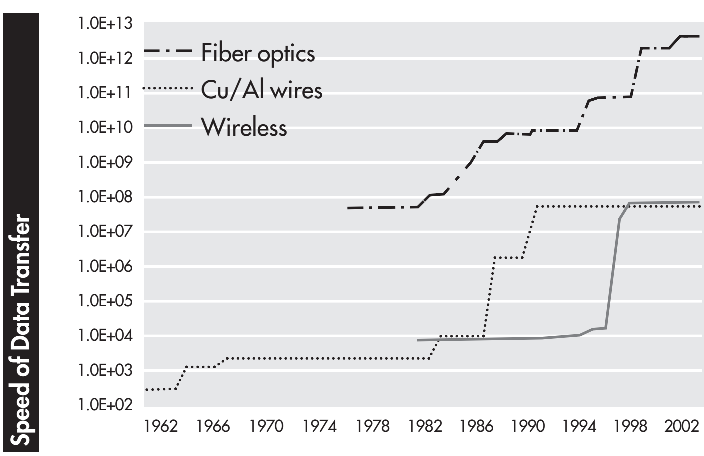
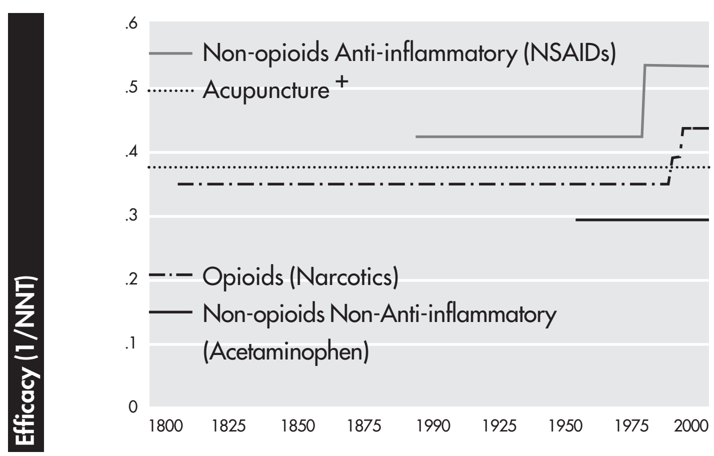


Figure 2f
Analgesics



* Performance on y-axis is in log scale, + Accurate performance records of efficacy of acupunture not available prior to 1971

Table 1
Primary Dimensions of Competition

Category	Primary Dimension	Metric
External lighting	Lighting efficacy	Lumens per watt
Desktop memory	Storage capacity	Bytes per square inch
Display monitors	Screen resolution	Dots per square inch
Desktop printers	Print resolution	Pixels per square inch
Data transfer	Speed of data transmission	Megabits per second
Analgesics	Absolute risk reduction (ARR)	Numbers needed to treat (NNT = 1/ARR)

Table 2a
Test of Logistic Fit for Technologies with Single S-curves

	Parameter Estimates	
Technology[1]	Upper Asymptote (*t*-value)	Growth rate (*t*-value)
Magnetic memory	4.28 (8.5)	.50 (24.8)
Optical memory	1.20 (7.4E + 06)	30.95 (24.2)
Magneto-optical memory	3.51 (5.2)	.51 (7.8)
Wireless data transfer	1.57 (234)	6.29 (5.3)
Opioid analgesics	4.40 (59.2)	.67 (15.9)
NSAIDs	1.93 (6658)	8.44 (26.6)

1. Acetaminophen, non-drug analgesics (acupuncture), and OLED displays were excluded from analysis

predict the probability and size of the performance jumps.

Identification of platform innovations and performance attributes

We identified various technologies in each of the markets, each of which was initiated by a platform innovation: five in external lighting, four each in desktop printing, display monitors, and analgesics, and three each in desktop memory and data transfer. Appendix A describes these technologies briefly. (Detailed definitions for these innovations are available in a technical note from the authors.)

We found that some of the platform technologies may not be readily distinguishable to the customers for one major reason. Even when a new technology differs radically from an old one, firms try to facilitate consumer adoption by maintaining a uniform interface for the new product based on the new technology. For example, lamps from different platform technologies such as incandescence or arc discharge use standard screw ends. We considered the underlying technologies as distinct if they are based on fundamentally different scientific principles. We adopted this rule so as not to confuse differences in technologies based on their characteristics with superficial differences based on derived products.

In each category, at a particular stage of technological evolution and consumer needs, certain dimensions of performance assume primacy. We did not have difficulty identifying these dimensions based on the historical description of the technologies and of what consumers then con-sidered important. Fortunately, each of the dimensions has fairly clear performance metrics. In choosing metrics, we were careful to take into account output per unit of input (see Table 1).

Shape of technological evolution

H1 hypothesized that technologies evolve through S-curves. We first plotted the performance of technologies on the y-axis against time on the x-axis (see figures 2a-f). As postulated by the hypothesis, these figures reveal that technologies do have a slow start and a sudden growth spurt.

However, in only 6 technologies do we find that the technology progresses along a single S-shaped path with a single inflection point followed by a permanent plateau or maturity. In 14 technologies we do not find a single S-curve. Rather we find long periods of static performance interspersed with abrupt jumps in performance. A visual examination of these plots suggests a series of S-curves or multiple

Technologies with Single S-Curve

Figure 3a
Optical Memory

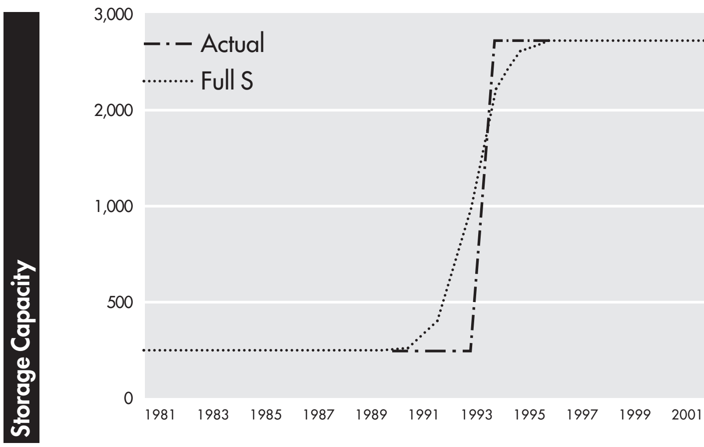
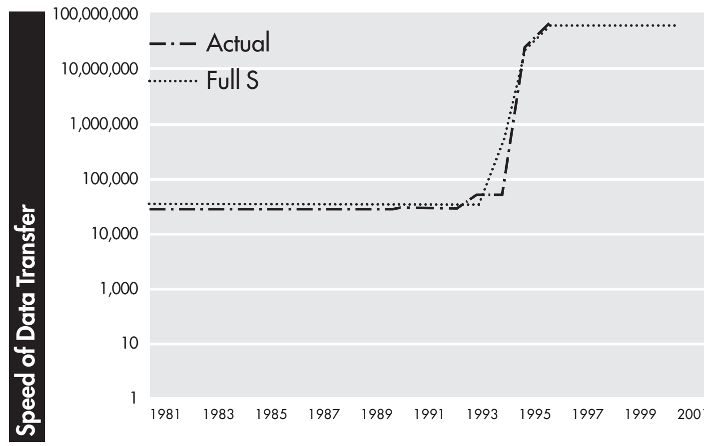


Figure 3b
Wireless Data Transfer



Technologies with Multiple S-Curves

Figure 3c
Incandescent Lighting

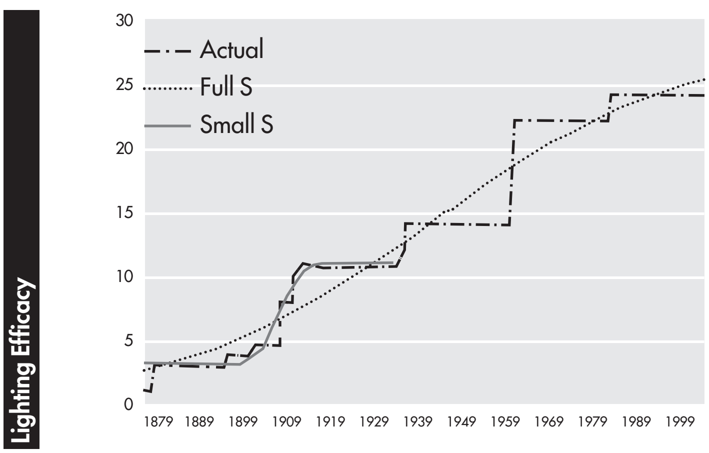
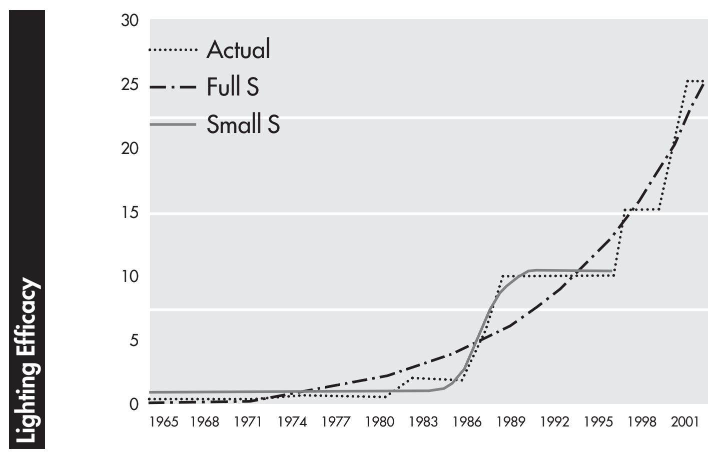


Figure 3d
LED Lighting



S-curves, with a new one starting at the point the earlier one seems to plateau. The figures suggest a series of step functions, each of which could approximate an S-curve.

Two technologies show no change in performance since introduction while one technology has only two data points. So we exclude these three technologies from the formal tests of shape. To formally test hypothesis H1 that evolution follows an S-shaped function, we carried out the following two tests:

First, we fit the generalized logistic function to the six technologies that reveal a single S-shaped curve:

$$Y_t = d + \frac{a}{1 + e^{-b(t-c)}} \tag{1}$$

Table 2b
Test of Logistic Fit for Technologies with Multiple S-Curves

Technology	Improvement in fit* of subsample over full data			
	Full data		Subsample	
	# Years	MSE	# Years	% Reduction
Incandescent lighting	123	.05	50	88%
Arc discharge lighting	94	.02	40	86%
Gas discharge lighting	70	.09	25	97%
LED lighting	37	.15	30	97%
MED lighting	13	.03	8	100%
Dot matrix printers	24	.04	14	95%
Inkjet printers	18	.05	13	97%
Laser printers	17	.02	10	100%
Thermal printers	11	.09	9	95%
CRT monitors	31	.09	27	97%
LCD monitors	19	.20	18	93%
PDP monitors	19	.14	7	100%
Copper/al cables	42	.57	21	95%
Fiber optics	27	.06	25	99%
Mean	**38.9**	-	**21.2**	**96%**

(* Measured as reduction in mean square error)

Where Y_t = performance of the technology in year t, and a, b, c, and d are parameters to be estimated: b is the growth rate, c is the time of maximum growth or the inflection point, and $a + d$ is the upper asymptote of the S-curve. We used the nonlinear regression techniques in SAS to estimate the model over the entire data.

Second, for technologies seeming to exhibit multiple S-curves, we fitted the generalized logistic function to both the entire series of data and to a subsample of data which exhibited an S-curve. We used two criteria to select a subset of data for this purpose: (1) performance of the technology during the subsample had an upper plateau that was longer in duration than the duration of the just preceding growth phase and (2) the subsequent jump in performance in the one year immediately after the plateau was almost double the performance during the entire plateau. In these cases, our practical goal is to test how well an S-curve fits on the whole sample and whether an S-curve on a subsample fits better than one on the whole data.

For the 6 technologies with an apparent single S-shaped curve, the generalized logistic function provides a very good fit with the data (see Table 2a and figures 3a-b). For the remaining 14 technologies which seemed to exhibit multiple S-curves, an S-shaped curve over a subsample of data fits better than one over the whole data, even after taking into account degrees of freedom (see Table 2b and figures 3c-d). Table 2b shows that the fit over the subsample gives an average reduction of 96% in the mean square error (MSE) from that over the whole sample. Further, Table 2c shows that the parameter estimates of the fitted generalized logistic function for the subsample are significantly different from the parameter estimates over the whole sample, after adjusting for degrees of freedom. For this test, we used the t-test for differences in parameters with unequal variances over the two models. Most importantly, the upper asymptote in the subsample is significantly and substantially different from that in the whole series, leading us to reject hypothesis H1 of a single S-shaped curve.

To summarize, the hypothesis of a single S-shaped growth in performance is supported for only 6 of the 22 technologies. For 2 technologies, performance does not change. For the remaining 14 technologies, change in performance follows a series of irregular step functions better approximated with multiple S-curves than a single S-curve. Across these step-functions within a technology, estimates of growth rate and especially performance at maturity (the upper asymptote) differ substantially. These findings are in line with James and Sood (2005) which adopt a different approach to test the hypotheses by testing for patterns in residuals.

These findings have important implications. An analyst expecting an S-shaped curve would conclude that the first curve (on the subsample) meets the hypothesis. He or she would then wrongly conclude that the technology has

Table 2c

Difference in Parameter Estimates for Technologies with Multiple S-Curves

Technology	Difference in Parameter Estimates: Upper Asymptote Difference (*t*-value)	Growth rate Difference (*t*-value)
Incandescent lighting	2.6 (182)	−.4 (−137)
Arc discharge lighting	2.9 (282)	.2 (71)
Gas discharge lighting	3.2 (141)	−7.4 (−36)
LED lighting	318 (43)	−1.3 (−80)
MED lighting	95.5 (731)	−20.4 (−52)
Dot matrix printers	2.2 (68)	−4.9 (−42)
Inkjet printers	2.6 (79)	−1.8 (−9)
Laser printers	1.6 (63)	−20.8 (−80)
Thermal printers	2.5 (14)	−7.2 (−14)
CRT monitors	97.3 (44)	−.2 (−11)
LCD monitors	89.6 (21)	−.4 (−11)
PDP monitors	1.1 (10)	−28.6 (−222)
Copper/aluminum cables	17.7 (425)	.6 (14)
Fiber optics	−1.6E + 12 (−3.0E + 08)	−12.6 (−19)

Table 3a

Performance of New Technology Relative to Old

Technology Category	Proportion of new technologies with low performance wrt old at introduction*	Proportion of new technologies with high performance wrt old at maturity^
External lighting	1/4	3/4
Desktop memory	0/2	1/2
Display monitors	3/3	1/3
Desktop printers	2/3	1/3
Data transfer	1/2	1/2
Analgesics	1/2	1/2
Total	**8/16**	**9/16**
Binomial test—probability technology performs as per H_{2a} /H_{2b}	*$p < .001$	^ $p < .001$

matured at the upper asymptote, when indeed it has not. As a result of this incorrect conclusion, the analyst would suggest abandoning the old technology. The average period for the subsample S-curves is 21 years compared to an average of 39 years for the full period. Thus this error may result in premature abandonment of a promising technology as early as at least 18 years before its life to-date. Substantial improvements in performance after the first plateau suggest the gravity of the error.

Performance of competing technologies

H2 hypothesizes three characteristics of technological competition—performance of new technology at introduction and at maturity (points 1 and 2 in Figure 1b) and a single crossing when the new technology crosses the old technology in performance. We tested each part of this hypothesis with a binomial test of the expected frequencies against observed frequencies. Our results are quite contrary to the hypotheses (see Table 3a).

The binomial test rejects both H2a and H2b ($p < .001$). A majority of new technologies performed better than the old technology, right from the time they were introduced. Also, many new technologies never improved over the old technology while others enjoyed brief spells of dominance over the old technology before the old technology regained dominance.

This unexpected pattern of evolution results in three distinct types of crossings between any pair of successive technologies (see Table 3b). First, 8 out of 16 technology pairs showed no crossing at all. In these cases new technologies either started higher than the old technology and remained higher or started lower than old technology and never crossed the old technology long after their introduction. Second, many technologies (4 out of 16) showed multiple crossings. In such cases, the new technology passed an older technology but was not able to sustain its advantage. Third, the expectation of a single crossing, of new passing the old from below, was satisfied in only 4 out of 16

Table 3b

Number of Crossings between New and Old Technologies

Technology Category

	Single	Multiple	No Crossing
External lighting	0	1 (2)*	3
Desktop memory	1	1 (3)*	0
Display monitors	1	1 (3)*	1
Desktop printers	2	1 (2)*	0
Data transfer	0	0	2
Analgesics	0	0	2
Total	**4/16**	**4/16**	**8/16**
Binomial test—probability no. of crossings as per H_{2c}	*$p < .001$	*$p < .001$	*$p < .001$

* Figures in brackets indicate the total number of crossings in the technology pair with multiple crossings

Table 4

Emergence of Secondary Dimensions of Competition

Market	Secondary Dimensions
External lighting	Brightness, color rendition, light efficacy, compactness, and life
Desktop memory	Areal density, reliability, and cost
Display monitors	Resolution, compactness, screen size, and efficacy
Desktop printers	Resolution, graphics, speed, and continuous color rendition
Data transfer	Transfer speed, bandwidth, and connectivity/mobility
Analgesics	Analgesia, reaction speed, targeted-action, and reduced side effects

technologies—a mere 25% rejecting the hypothesis H2c of a single crossing ($p < .001$) using the binomial test of differences.

In summary, we find no support for any of the three sub-hypotheses on performance of competing technologies. So the final status of each technology cannot be determined solely from the direction of the attack or timing of introduction. As such, it would be unwise for an incumbent to scan for competition only among technologies performing worse than its current technology and to make decisions on that basis.

Progress on secondary dimensions

We find that new technologies typically perform better than old technologies on some secondary dimension. This new dimension also affected the basis of competition in these markets. For example CRT monitors were emphasizing resolution prior to LCDs. However, LCDs were inferior in resolution but superior in lightness to CRTs. After their introduction, the two technologies competed on dual dimensions of resolution and lightness. These findings are consistent with Christensen's (1999) assertion about emergence of new dimensions.

In contrast to H3 which proposes only generic dimensions, our results suggest a sequence of random, unpredictable secondary dimensions in each of the six categories. Each platform technology offered a completely new secondary dimension of competition while still competing on the primary dimension. These dimensions are supposed to form the basis of inter-technological competition as well as the basis of consumer choice.

For example, consider four successive technologies in monitors: CRT, LCD, plasma, and OLED. CRT monitors were initially introduced on the basis of resolution. The new LCD monitors were inferior on resolution but were stronger on a new but important secondary dimension: thinness and weight. The new plasma display panels were inferior in resolution to both the prior technologies, but were superior on a tertiary dimension, large screen size. The new OLED displays were inferior to the prior three technologies in resolution but were superior in efficacy. Hence, each technology in display monitors emphasized a new dimension, on which it was superior: resolution, compactness, screen size, and efficacy.

Similarly, we identified the emergence of a new secondary dimension in each of the other categories (see Table 4). Again none of these have any resemblance to the generic dimensions proposed by Christensen (1999) and represented by H3. We also found that technologies

Figure 4a
Declining Time between Introduction of New Platform Innovations

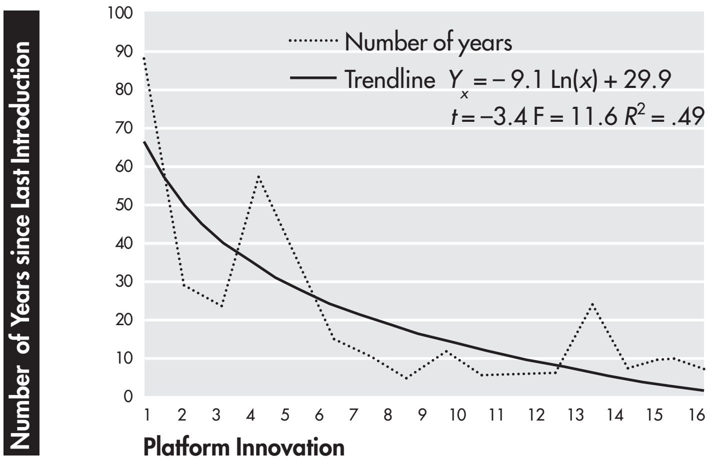


Figure 4b
Declining Duration between Successive Improvements within Technology

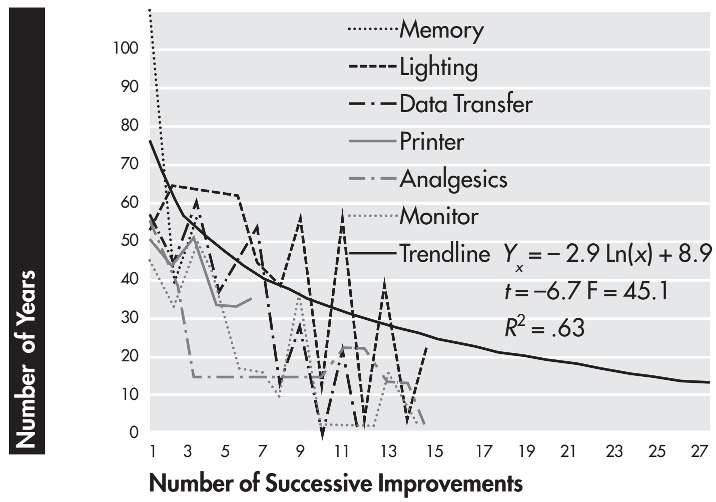
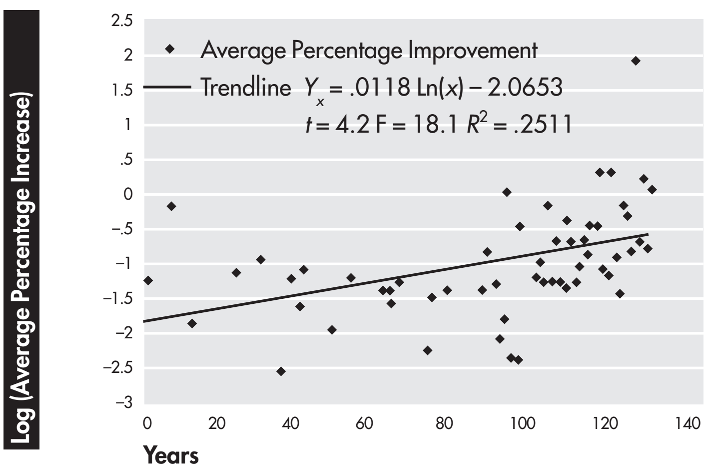


Figure 4c
Increasing Average Percentage Improvment over Last Year



that excel in a particular dimension cater to particular segments that value that dimension. When the mass market focuses on one old or new dimension, niche markets, interested in the other dimensions, might still survive. For example, LED lighting has carved a niche in automobile, signage, and contour lighting applications; MED lighting is the popular choice in applications where lamp replacement is difficult because of accessibility.

In summary, we find that though new technologies perform better than old technologies on secondary dimensions, the competition evolves in new, unpredictable secondary dimensions instead of the standard four generic dimensions proposed by literature.

Pace of technological transition

The alternative hypotheses H4o and H4a state that the pace of technological transition is either constant or increasing, respectively. Past findings in the literature on this issue are neither consistent nor use direct measures. To test these hypotheses, we used three direct measures of the rate of technological change:

- The pace of introduction of new technologies, for each of the six categories, calculated as the number of years between successive introductions.
- The pace of technological improvements within each platform, calculated as the number of years between (non-zero) improvements in technological performance.
- The annual rate of improvement for each technology, calculated as the percentage increase in performance over the past year.

Tests of all three measures support an increasing pace of technological change (see figures 4a-c). The negative slopes of trends for both the measures of duration suggest declining duration between introductions of successive new technologies as well as declining duration between successive improvements in each technology. The positive slope of trend for the rate of improvement over last year suggests an increase in the pace of technological change.

To formally test the alternate hypotheses, H4o and H4a, we pooled the categories and estimated the following regression equation for each of the three measures.

$$Y_x = \alpha + \beta \log(t) + \varepsilon_t \tag{2}$$

Where Y_x represents each one of the above three measures of pace of technological change in year x, α and β are coefficients to be estimated, and ε_t are the errors assumed to be IID normal. The coefficients are significantly different from 0 for all three measures at $p <$ .001 level. Thus, we are led to reject the null hypothesis, H4o, that the rate of technological change is constant over time.

Note that our test is in the same spirit as meta-analyses which pool estimates across multiple categories (Assmus, Farley, and Lehmann 1984; Tellis 1988). Such pooling increases the power of the test and reduces the probability of a Type II error.

Source of new technologies

The dominant view in the literature is that new technologies come primarily from small entrants. To throw more light on this issue, we first operationalized incumbency and size. An incumbent is a firm that was in the category prior to the introduction of the new platform technology. All other firms are entrants. We classified a firm as small if the firm came into existence just prior to the introduction of a particular technology, which was also its first introduction. All other firms were classified as large.

In contrast to the dominant view in the literature (H5), we find that the source of platform innovations is almost equally from small entrants (12) and large incumbents (10). Large entrants account for only six, and small incumbents for none of such innovations respectively. While our results run counter to the dominant view in the literature, they are consistent with two recent findings in the literature (Sorescu, Chandy, and Prabhu 2003; Chandy and Tellis 2000). The probable reason is that in recent decades, innovation has gotten far more complex. The deeper pockets of large firms enable incumbents to maintain state-of-art facilities to conduct research while incumbency provides them with opportunity and resources for developing and introducing platform innovations. This reason is further supported by the fact that of the 10 innovations introduced by incumbents, none of them was introduced by small incumbents.

Towards a new predictive model

The empirical findings above lead to a rejection of the widely accepted S-shape of technological evolution. They strongly suggest that most technologies evolve through irregular step functions with jumps in performance or sudden improvements occurring after many years of static performance. Are the timings and size of these jumps entirely random or is there a pattern to them? If so, is the pattern explainable or predictable? To answer these questions, we modeled the probability of a jump (Y_1^*) and the size of the jump in a particular year (Y_2) as a function of some explanatory variables (X), thus:

$$Y_1^* = \frac{e^{X'\delta}}{1 + e^{X'\delta}} + U \tag{3}$$

$$Y_2 = X'\beta + V$$

$$(U,V) \sim N(0,\begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{bmatrix}) \tag{4}$$

We observe $Y_1 = 1(Y_1^* > 0)$ and X always, but

Table 5
Modeling Probability and Size of Jump in Performance

Variable	Probability of Jump	Size of Jump in Performance
Current performance	–.006 (–.07)	1.9 (30)
No. of prior crossings	–.17 (–1.4)	–1.05 (–11.4)
Order of entry	.26 (.5)	–.6 (–10.9)
No. of prior jumps	.06 (3.1)	–.18 (–11.3)
Current year	.001 (.4)	.01 (5.5)
Time since last jump	–.96 (–9.6)	.03 (3.5)
Jump in rival	.46 (2.5)	–.3 (–2.3)
Mills	-	.09 (2.6)
% reduction in uncertainty (Rho^2)	62%	-
Adj-R^2	-	61%

Note: *t*-values in parentheses

observe Y_2 only when $Y_1 = 1$. We estimated the joint outcome – probability and size of jump - using the Tobit (Type II) model (Tellis 1988; Maddala 1983; Amemiya 1985). This formulation eliminates the sample selection bias introduced from observing the size of a jump on only those events where the probability of a jump is 1. The explanatory variables in X are from two broad categories – factors directly related to the intrinsic characteristics of the technology and factors related to the existing competition in the category. We first standardized the performance in order to pool across categories and then calculated the size of jump relative to the preceding year. The results are in Table 5. The Rho^2 (reduction in uncertainty) is 62% for the first stage model and the R^2 (explained variation) is 61% for the second stage model. The best predictors of the probability of a jump are length of time since last jump (–), a jump in a rival technology (+), and the number of prior jumps (+). The best predictors of the joint event of probability and size given a jump are current performance of the technology (+), time since last jump (+), number of prior crossings between rival technologies (–), order of entry in category (–), current year (+), and number of prior jumps in the technology (–). These results together with the earlier ones suggest that the improvement in technological performance neither follows an S-shaped curve nor is it entirely random. Rather, improvement in performance follows some patterns that are somewhat predictable. In general, size of the jump increases with newer technologies and with those that have higher performance. The probability of a jump also increases with a jump in a rival technology. Most important, a plateau in performance by itself does not imply a technology has matured. Indeed, the longer the plateau the higher the expected net jump in performance. Thus, the past pattern of performance may have clues about the future performance, though it may not follow the path of a single S-shaped curve.

Discussion

This section summarizes the findings and discusses questions, implications, and limitations of this study.

Summary of findings

The current research leads to six major findings:

- Technologies do not show evidence of a single S-shaped curve of performance improvement. Rather they evolve through an irregular step function with long periods of no growth in performance interspersed with performance jumps. A jump in performance appears to be largest after a long plateau of no improvement.
- New technologies may enter above or below the performance of existing technologies. The performance curves of a pair of competing technologies rarely have a single crossing.
- The path of technological evolution seems partially predictable. Past improvement in performance of the same technology, improvement or crossing by a rival technology, and especially crossing by a rival firm tend to signal immediate improvement in performance.
- Each new technology introduces a sequence of random, so far unpredictable secondary

dimensions as a new basis of competition.

- The rate of technological change and number of new technologies is increasing over the time.
- New technologies come as much from new entrants as from large incumbents.

Questions and further analysis

Our results are based on comparing a technology with the one introduced just prior to it. One might ask if these results are in any way sensitive to the reference point of the comparison technology. We redid all our analysis using the first technology and the dominant technology in the category. The results were not materially different from those reported here.

We also examined the gestation period of each technology, defined as the time it takes for a firm to convert a patent to a commercial product. The average gestation period for technologies is 15.8 years for external lighting, 14.5 years for display monitors, 14.3 years for desktop printers, 9.7 years for desktop memory, 22.7 years for data transfer technologies, and 67 years for analgesics. The overall average for all categories is 22.3 years. (We again had to exclude acupuncture from the calculation of gestation period as it is difficult to ascertain the exact date of introduction of this technology.) Given this long gestation period, our results show that investors need to be patient and managers need to persevere in order to bring a new technology to fruition.

Fourth, we examined whether the gestation period is shrinking over time given the increasing pace of technological change. In order to examine this hypothesis, we did a median split of the gestation period by the year 1970. Each of the groups had technologies from all six categories. An analysis of the mean gestation periods of the two groups revealed a large and significant difference between the pre-1970 set (average 30 years) and post-1970 set (average 14 years) of 16 years (t = 2.10).

Finally, to check whether these results were at the cost of a censoring bias from not allowing enough time for the new technology to improve, we compared the time taken for the technologies that failed to cross old technologies with those that did. The average number of years for new technologies to reach the point of first crossing the old technology is 4.2 years. In contrast, categories in which the new technology never crossed the old have been in existence for 18.3 years. Hence, the lack of a crossing cannot be due to not leaving enough time or for a censored time frame.

Survival bias

Does survival bias affect our results? It is impossible to rule out survival bias, albeit we took great pains to minimize its role. First, we tried to include every technology that was commercialized in the markets that we covered for the time period that we studied. Second, to examine the possible effect of inadvertently excluding any technologies from the analyses, we define two categories of technological failures—non-starters and stagnant technologies. Non-starters are those that were used in related fields, could have been used in the target markets with some modification, but were never used. In other words, these are potential technologies that were never commercialized. On the other hand, stagnant technologies are those that fail to show improvements in performance, cost, and features. Stagnant technologies were selectively used in these markets at first but were never successful beyond the initial introduction because of this failure to improve. Examples are combustion-based lighting technologies like candles or oil-based lamps. The key issue is whether our exclusion of failures, so defined, biases our results, just as survival bias upwardly biases the alleged advantages of market pioneers (Golder and Tellis 1993).

We believe that non-starters do not affect any of our results for three reasons. First, in the pioneering literature, failures are firms that did commercialize a product but are no longer surviving. Our definition of non-starters is much more stringent—they are technologies

Figure 5a
Desktop Printer Technologies—Resolution per Dollar

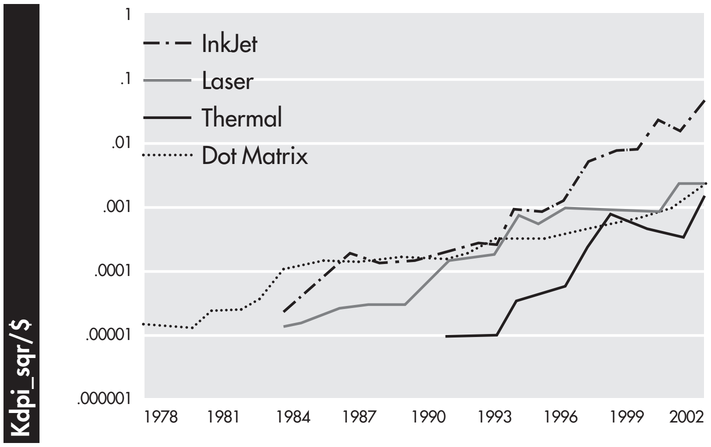


Figure 5b
Desktop Memory Technologies—Storage Capacity per Dollar

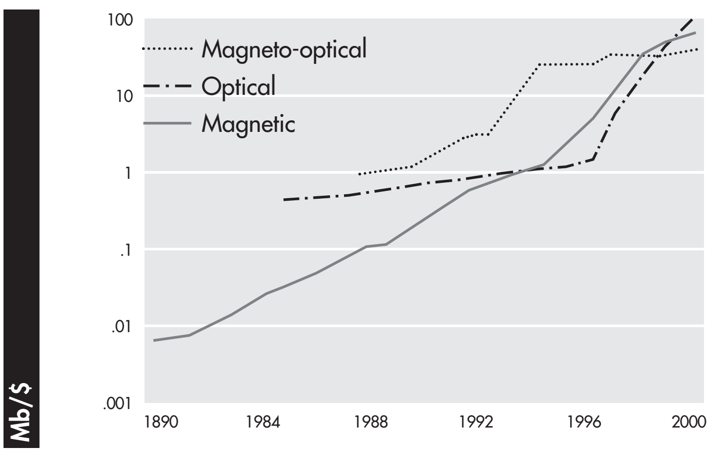
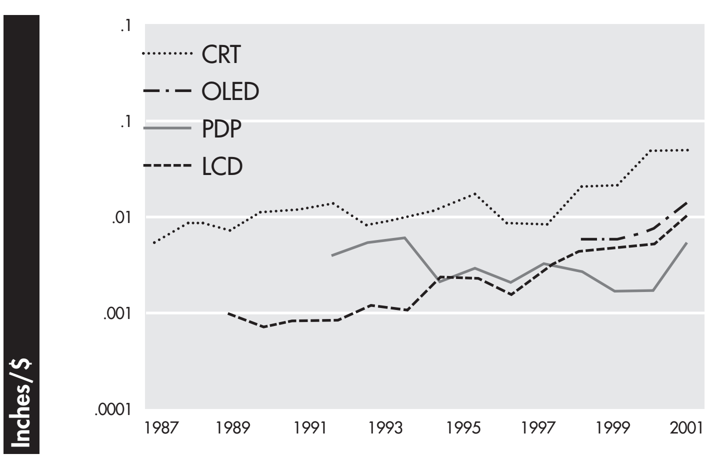


Figure 5c
Display Monitor Technologies—Size per Dollar



that were never commercialized. Second, most of our analysis tracks the progress of individual technologies without averaging performance across technologies. As such, the exclusion of non-starters does not bias computed performance levels (as it does when computing market share performance of only surviving market pioneers). Third, our entire analysis tracks the performance of a technology given that it was commercialized. We do not make any predictions or test any hypotheses about the productivity of R&D, in which case non-starters would loom large.

To ascertain what insights might be gleaned from a consideration of stagnant technologies, we explored the histories of the three such technologies from three categories—arc lamps in external lighting, chain printers in desktop printers, and wire recorders in desktop memory. (Details of these technologies are available from the authors.) We find common factors in each of these cases. First, each of the stagnant technologies failed to develop an acceptable standard or be included in a prevailing standard, e.g., wire recorders were excluded from the standard-setting process in favor of magnetic tape technology by the recording industry. Such exclusion in the standards-setting process, also termed technological lockout (Schilling 1998), leaves the technology in a weak market position (Shapiro and Varian 1999). Second, a new and better technology was either introduced very early in the life of stagnant technology (e.g., magnetic tape and wire recorders, dot matrix printers and chain printers etc.), or the performance of new technology was exceptionally superior to (or growing at a fast rate than) the stagnant technology (e.g., incandescent lamps and kerosene lamps). Perhaps as a result of these two factors, the stagnant technology did not show any improvement in performance on all dimensions that we tracked.

The exclusion of these technologies does not lend support to any the alternative hypotheses that we tested and rejected, such as a single S-shaped curve, single crossing, or generic dimensions of competition. However, since stagnant technologies were excluded, it would be wrong to conclude from our results that performance always improves over time.

Performance per unit price

Some authors propose that, when testing the S-curves, benefits per dollar should be used as the key dependent variable instead of performance (Chandy and Tellis 1998). Although all our current performance measures also have a denominator for proper scaling (e.g., Lumens per watt) we investigate the sensitivity of our results to using this alternate metric.

We collected data on benefits per dollar for three categories—desktop printers, desktop memory, and display monitors. For each technology, we identified the product offering the highest benefit per year and the price at which it was offered at introduction. The results in figures 5a-c do not provide support to any of the hypotheses that we rejected. For example, we observe multiple crossings in all categories, and new technologies being introduced with higher benefits per dollar. Moreover we found that the evolution of technologies is not even a monotonic function of benefits per dollar. One possible reason is that firms charge higher prices for technologically advanced products until competition drives the price down.

Multi-attribute performance

Some might question whether our results hold when we take into account multiple dimensions of performance simultaneously. To clarify this issue, we repeated the analysis using multiple dimensions in two categories: desktop printers and display monitors. For printers, we collected data on speed of printers measured as pages per minute (PPM) in addition to print resolution. For monitors we collected data on screen size measured in diagonal inches in addition to resolution. Note that our findings on shape, path, and crossing patterns are quite robust to the use of this second dimension (see figures 6a-b).

We also calculated standardized values of performance on each dimension over the category for each platform, computed the sum of these standardized values over all dimensions of performance, and then plotted the latter index by time (see figures 6c-d). The use of multiple dimensions simultaneously using this crude index fails to yield any patterns that might support the theory of S-curves.

Implications

This study has several implications for managers.

First, using the S-curve to predict the performance of a technology is quite risky and may be misleading for two reasons: One, most of the technologies do not demonstrate an S-shaped performance curve. Two, several technologies show multiple S-curves, suggesting that a technology can show fresh growth after a period of slow or no improvement.

Second, the continuous emergence of new technologies and the steady growth of most technologies suggest that relying on the status quo is deadly for any firm. Moreover, technological progress is occurring at an ever-increasing pace. As such, paranoia rather than complacency is healthy. Vigilance for the emergence of new technologies coupled with efforts to improve the old technology can help an incumbent sustain and advance its position or even preempt competitors.

Third, the present findings indicate that the attack from below remains a viable threat. Many new technologies start by offering low performance but later threaten old technologies by improving at a much faster rate. Incumbents are prone to disregard these new technologies initially, because they often cater only to a niche and not to the mass market. However, these niches can grow into mass markets eventually replacing the old technology. Thus, this disregard of such new technologies is particularly dangerous. Further, some new technologies can perform better than old technologies even at the time of introduction.

Fourth, another threat to incumbents is the

Figure 6a
Performance of Desktop Printer Technologies on Speed

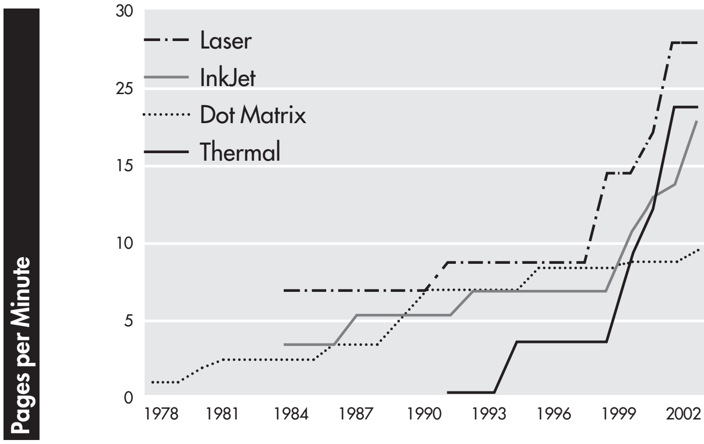


Figure 6b
Performance of Desktop Monitor Technologies on Screen Size

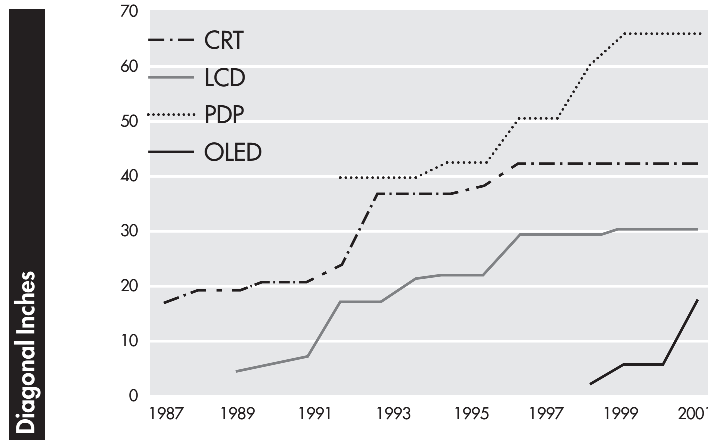


Figure 6c
Multi-attribute Performance of Desktop Printer Technologies

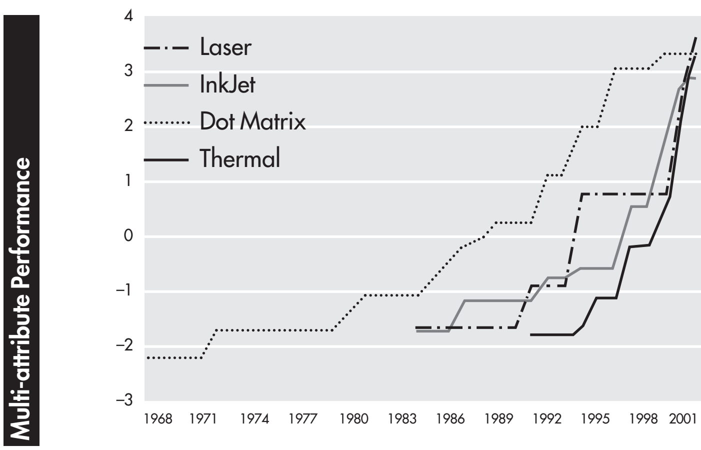
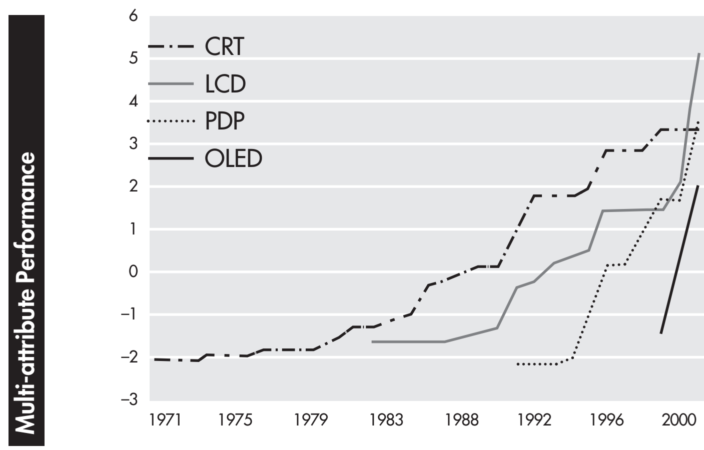


Figure 6d
Multi-attribute Performance of Display Monitor Technologies



emergence of secondary dimensions of competition. Old technologies may be completely vulnerable to these dimensions. Faced with such threats, incumbents need research to identify technological solutions to improve the value of the old technology as well as to identify market segments that value the contributions of the old technology. Alternatively, incumbents need to explore R&D options on multiple dimensions in order to react appropriately to threats posed by entrants.

Fifth, first-mover advantages may not be lasting since entrants introduce even more innovations than incumbent firms. However, we found that old technologies demonstrated high levels of improvement even after being dormant and static for many decades. In some cases, old technologies regained dominance in performance even after being surpassed by a new technology. In contrast, a misplaced belief in the theory of S-curves might become a self-fulfilling prophecy and lead to the premature demise of an old technology.

Limitations and discussions for future research

This study has several limitations. First we had to limit our analysis to only six categories due to the time-consuming nature and difficulty of data collection. Second, our analysis of performance did not include cost to buyers. Third, we did not incorporate sales of products based on each technology within a category. All of these limitations are potential opportunities for future research. In addition, future research may also explore whether the theory of S-curves applies at the sub-platform level, why there are long periods of no improvement in performance, and how firms should compete given the pattern of technological evolution. ■

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Appendix A. Operating Principles of Sampled Technologies

	Technology	Principle
	External lighting	
1	Incandescent	Generates light by heating up thin metallic wires with an electric current
2	Arc discharge	Emits light by arc formed between two electrodes oppositely charged by an electric current in a high-pressure gas chamber
3	Gas discharge	Electrons excited by passing an electric current in a low-pressure gas chamber emit light
4	Light emitting diode (LED)	Emission of the light in n-p transition zone under influence of an electric potential
5	Microwave electrodeless discharge (MED)	Emission of light by microwaves from induction coil inside the bulb to excite the gas
	Desktop Memory	
1	Magnetic	Records data by passing a frequency modulated (FM) current through the disk drive's magnetic head thereby generating a magnetic field that magnetizes the particles of the disk's recording surface
2	Optical	Stores data using the laser modulation system and changes in reflectivity are used to store and retrieve data
3	Magneto-optical	Records data using the magnetic-field modulation system but reads the data with a laser beam
	Display Monitors	
1	Cathode ray tube (CRT)	Forms an image when electrons, fired from the electron gun, converge to strike a screen coated with phosphors of different colors
2	Liquid crystal display (LCD)	Creates an image by passing light through molecular structures of liquid crystals
3	Plasma display panel (PDP)	Generates images by passing a high voltage through a low-pressure electrically neutral highly ionized atmosphere utilizing the polarizing properties of light
	Desktop Printers	
1	Dot matrix	Creates an image by striking pins against an ink ribbon to print closely spaced dots that form the desired image

2	Inkjet	Forms images by spraying ionized ink at a sheet of paper through micro-nozzles
3	Laser	Forms an image on a photosensitive surface using electrostatic charges, then transfers the image onto a paper using toners, and then heats the paper to make the image permanent
4	Thermal	Forms images on paper by heating ink through sublimation or phase change processes.
	Data Transfer	
1	Copper/aluminum	Transmits data in the form of electrical energy as analog or digital signals
2	Fiber optics	Transmits data in the form of light pulses through a thin strand of glass using the principles of total internal reflection
3	Wireless	Encodes data in the form of a sine wave and transmits it with radio waves using a transmitter-receiver combination
	Analgesics	
1	Opioids (narcotics)	Reduces generation of pain signals by inhibiting the action of Cox enzymes responsible for inflammation
2	Non-opioids anti-inflammatory drugs (NSAIDs)	Reduces brain sensitivity to pain by imitating the body's own pain-killing chemicals and binding to pain-sensing sites throughout the brain
3	Non-opioids non-anti-inflammatory drugs (acetaminophen)	Preferential inhibition of pain by disrupting the activation of Cox enzymes
4	Non-drug pain treatments (acupuncture)	Alleviates pain by correcting the imbalance of qi (pronounced "chee"), a type of life force, with needles inserted at points along the energy pathways in the body

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