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Predictors of the Survival of Innovations*

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This article examines the impact of key success factors on the survival of innovations that have reached the market and were developed by inventors outside of established organizations. It is of interest to learn which characteristics predict, at an early stage, the duration of the innovation's length of sales, because this duration is important to the financial success of new products. A focus on survival also can contribute conceptual clarity to the study of new product development. This study uses the Inventor's Assistance Program (IAP) at the Canadian Innovation Centre (CIC) in Waterloo, Canada, as the source of data. The CIC is a not-for-profit agency that provides various services to foster business development involving innovative products and services. Analysts in the IAP evaluate a specific product idea or invention on 37 dimensions before it has reached the market. The data for the present study involved these 37 variables evaluated each with a three-point linguistic scale. As the evaluations of the criteria are subjective, they might be argued to contain inaccuracies compared to objective data. On the other hand, the analysts use multiple related measures of concepts that have been shown to increase predictive accuracy. The use of experts who are unrelated to the projects avoids decision-making biases potentially associated with project managers' assessment of their own projects, such as unrealistic optimism. The recording of the expert evaluations of the ideas before they reached the market and independent of the measure of success, rather than using post-project completion evaluations, eliminates measurement biases such as hindsight bias and common method variance bias. Identifying information was used in these records to conduct a telephone survey of the inventors. An exploratory method of data analysis is identified and used that distinguishes research-appropriate constructs and their indicators in these data. Cluster analysis was performed, and survival regression correlated cluster scores with survival. Three variables were found to significantly affect survival: anticipated stable demand, price required for profitability, and technical product maturity. In addition, the degree of competition had a marginally significant effect. Because these variables can be assessed at an early stage of an inventions' development, the expected survival time for a specific invention may be computed by entering these assessment values into the described survival model. Then this and other information may be used to compute the expected return of an invention.

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Introduction

An early-stage evaluation of the potential merits of an innovation has been shown to have considerable value (Mansfield et al., 1977, pp. 25–32). It is of interest to learn which characteristics predict, at an early stage, the duration of the innovation's length of sales, because this duration is important to the financial success of new products. While there has been extensive research on the predictors of project success (and failure) of innovations and new products (reviews by Balachandra and Friar, 1997; Henard and Szymanski, 2001; Montoya-Weiss and Calantone, 1994), little research can be located on the determinants of innovations' survival. Information about these determinants would have direct managerial implications for the evaluation of new product development (NPD) projects.

A focus on survival also can contribute conceptual clarity to the study of NPD. Most studies use fuzzy or sometimes no definition of new product success, allowing the research participants to interpret the outcome variable "success." This produces both measurement error and theoretical ambiguity. New product success entails at least three criteria or outcomes: whether the product reaches the market (commercialization), how long the product remains on the market (survival), and yearly profits. These success criteria may not necessarily correlate. For example, a product that early on earns high yearly profits may not have a long shelf life due to entry of imitators. It therefore makes good sense to study each of the three success criteria separately to learn more about the drivers of total returns.

This study examines the impact of key success factors on the survival of innovations that have reached the market and were developed by inventors outside of established organizations. Inventors are important sources of invention and economic renewal in society (Schumpeter, 1934) and thus merit attention in their own right. In addition, to the extent that new product success depends upon product and market characteristics, distinct from organizational factors (such as fit to a corporation's other products and services), this research should shed some light on factors in product survival more generally.

Of course, there are important differences between inventor and corporate product development. However, some of these differences imply that there may be unique benefit to using independent inventions for research focused on product and market predictors of survival. Independent inventors operate outside of established organizations and thus do not suffer from the decision-making biases often associated with established firms (Henderson, 1993; Henderson and Clark, 1990). Consequently, the products offered to the market by independent inventors may be somewhat different in their features from those offered by corporations, providing opportunities to detect the influences of these features.

The present study uses the Inventor's Assistance Program (IAP) at the Canadian Innovation Centre (CIC) in Waterloo, Canada, as the source of data on NPD projects by independent inventors. The CIC is a not-for-profit agency that provides various services to foster business development involving innovative products and services. Analysts in the IAP evaluate

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Dr. John Michela is with the Department of Psychology at the University of Waterloo. Employees' perceptions and motivations, especially as affected by interactions in groups or teams, with peers and leaders, is the overall focus of his research. Organizational culture, climate, and leadership are some of the constructs and domains of management literature that provide starting points for this research. Most recently he has studied relations of these and related constructs with organizational and individual performance for quality and innovation, and previously with stress. Because research methods for studying these matters often are insufficient, research methodology is another aspect of his work. Dr. Michela has recently published in the *Handbook of Organizational Culture and Climate* and the *Journal of Personality and Social Psychology*. John's training and consulting span various topics in the fields of organizational and team development, organizational research methods, quality management, and employee selection and development. Dr. Michela has a Ph.D. in social psychology from University of California–Los Angeles and taught at Columbia University for nine years prior to joining Waterloo.

a specific product idea or invention before it has reached the market. The purpose of this evaluation is to advise the potential entrepreneur on whether and how to continue efforts. [For further descriptions see Åstebro and Gerchak (2001), Udell (1989), and Udell, Bottin, and Glass (1993).]

Analysts from the IAP use a fixed set of 37 criteria, each with a three-point linguistic scale, to evaluate each new product idea. As the evaluations of the criteria are subjective, they might be argued to contain inaccuracies compared to objective data (Henard and Szymanski, 2001). On the other hand, the analysts use multiple related measures of concepts that have been shown to increase predictive accuracy (Henard and Szymanski, 2001). The use of experts who are unrelated to the projects avoids decision-making biases potentially associated with project managers' assessment of their own projects, such as unrealistic optimism (Armor and Taylor, 2002) and hindsight bias (Fischhoff, 1975). The recording of the expert evaluations of the ideas before they reached the market and independent of the measure of success, rather than using post-project completion evaluations, eliminates measurement biases such as hindsight bias and common method variance bias (Campbell and Fiske, 1959; Fischhoff, 1975).

Key Success Factors for New Products

There has been a great deal of research on the determinants of new product success. Reviews can be found in Balachandra and Friar (1997), Henard and Szymanski (2001), Lilien and Yoon (1989), Linton, Walsh, and Morabito (2002), and Montoya-Weiss and Calantone (1994). The factors studied can be organized in the overall categories of product characteristics, organizational development process, firm strategy, and market factors (Henard and Szymanski, 2001). Research and meta-analyses have provided considerable evidence that a great number of factors within these categories can influence the outcomes of new product development.

An example of this tradition is Cooper (1981), who conducted a retrospective survey of 195 new product projects to determine the factors perceived by research and development (R&D) managers to be associated with perceived success. A factor analysis was conducted on 48 variables to generate a smaller and more manageable subset of factors. Thirteen factors explained 69.3 percent of the variance of the original 48 variables. A total of 7 of the 13 factors were significantly related to perceived project success at least at the 0.10 level. The model had an R^2 of 0.42 and correctly predicted 84.1 percent of the projects' outcomes in a naive split-sample test.

However, this study found little common agreement with others as to the relevant success factors identified by Balachandra and Friar (1997). Performing a meta-analysis of 60 research publications, these reviewers find contradictory results and little stability regarding the significant determinants of success across these studies; in addition there seems to be no clear agreement even on the direction of influence of the factors analyzed. Balachandra and Friar (1997) noted four major sources of weakness in the studies on the success or failure of new product development and R&D projects, namely the quality of data (low), the definition of a new product (fuzzy), factor selection and definition (weak reliability and validity, small samples), and measurement of factors (unclear, not standardized).

Henard and Szymanski (2001) found the following from their meta-analysis of 41 studies of 24 antecedents that were reported frequently enough to permit meaningful investigation:

- In multivariate analysis the significant and dominant drivers are relatively few: product advantage, product innovativeness, marketing synergy, technological synergy, market orientation and competitive response intensity, with product advantage and technological synergy explaining the most variance.
- A few select variables explains most of the variance—there is no need to measure a large number of factors.
- Multi-item measures are more predictive than single-item measures.
- The length of time that defines project success determines the importance of several factors.
- Objective performance data yield stronger relationships than subjective performance data.

Different measures of *success* have been used. Cooper and Kleinschmidt (1987) identified three measures of success: financial performance, opportunity window, and market share. Lilien and Yoon (1989) and Griffin and Page (1993) added other dimensions. It is acknowledged here that project success is a multidimensional concept. This study's purpose is to analyze a single well-defined and objective outcome measure: the length of survival of an innovation in the marketplace.

Focusing on the survival of new products, Asplund and Sandin (1999) discovered that new beer brands with low and decreasing market shares have higher hazard rates and that products from firms with the largest market shares face a greater risk of being withdrawn. The first result is theorized to depend on the unpredictable nature of consumer demand, where firms gradually learn about preferences over time (Jovanovic, 1982). The second result may be product market specific. Results may be attributed to large beer producers trying to squeeze out smaller producers by repeatedly releasing (and withdrawing) new products (Schmalensee, 1978). Interestingly, Asplund and Sandin (1999) could not reject the hypothesis of a constant hazard over time implying an exponential duration distribution.

The Present Study

The data for the present study involved 37 variables conceived by the IAP to be success factors for new products. Most of these variables have been investigated previously. In fact, the variables included in the original instrument were derived by Udell (for an overview see Udell, 1989) based on research in the early 1970s that was current when the original IAP instrument was constructed. Appendix A lists the 37 variables.

Approximately half of the members of this set of variables are labeled in Appendix A as *market* factors. Several of these variables, in the subcategory of *demand*, are straight from the economics literature (e.g., Mansfield, 1968) and involve factors known to affect the diffusion of innovations (size of market, growth of demand, duration of demand, demand predictability, product line potential).

The greater the demand, demand growth, and duration of demand, the greater the sales opportunities and thus prospects for remaining profitable in the market. Uncertainty of demand and product line potential also could play a role in determining survival. Given stochastic demand and a fixed cost in each period (for example debt repayments), then greater demand uncertainty leads to greater probability that demand will not be able to support the fixed costs in any given time period (and shorter expected survival). Also, if demand fluctuates from year to year for any given product line, then the greater the number of product lines, the lower the probability that a significant drop in demand for a single product line will cause an inventor to discontinue sales of the innovation altogether. That is, greater applicability across a number of products or services provides for risk spreading and reduces the hazard of exit due to random market events. Note that the uncertainty of demand and product line potential does not necessarily affect the probability of commercialization unless one assumes the decision-maker to be risk averse. These factors therefore may have a differential impact on innovation survival compared to invention commercialization, and the differential impact depends on risk preferences.

The *acceptability* factors are derived from research on the psychology/sociology of innovation adoption (Rogers, 1995) (need, societal benefits, compatibility, learning, visibility, appearance, comparative functionality, and durability). While these were conceptualized to condition the adoption decision of individuals, they also may affect the duration of innovations' survival. If adopters' decisions are distributed over time, the greater acceptability will increase the probability of adoption at any point in time thus increasing the sales also in later years, marginally increasing survival.

The industrial organization literature predicts that industry structure (existing competition, new competition) affects price and thus profits (Scherer and Ross, 1990). Also relevant to price and competition is protection (through patents, trade secrets, and so forth), which indicates the degree to which the inventor can capture monopolistic rents (Cohen, 1995). Higher profits, either through industry structure, price, or intellectual property (IP) protection, would lead to longer survival duration.

Innovations arrive in the marketplace with different technical solutions, and producers only learn consumers' preferences over time (Jovanovic, 1982). Inferior, or less developed, products may be released on the market but, once released, have greater likelihood of being discontinued in each successive time period as better solutions attract higher demand. It thus would seem reasonable that the technical factors (technical feasibility, functional performance, research and development, technology significance) and the production factor "technology of production" would affect survival. Further, a lower absolute investment for entry should lead to a higher probability of exit (Åstebro and Simons, 2003). A lower absolute investment for entry means there are more marginal inventors entering—inventors who would be the first to exit. Note that the effect of the size of the initial investment is proposed to be negative on commercialization but positive on survival duration (Åstebro and Simons, 2003).

Several product variables available in the data, such as expected safety and environmental impact, were included in this study's analyses even though they may not have much variation. For example, the rate of severe safety problems—sufficient to affect survival—may be too low in order to detect their effects in research like the present. One further reason to expect different predictors of survival as compared to commercialization is that the range of variables drops when products with less favorable values are kept off the market, and the remaining products then survive with varying durations. For the same reasons then, finding significant predictors for survival might be more difficult than finding predictors of successful commercialization.

Data Collection

The sample frame for survival analysis consisted of all valid records of inventions submitted to the IAP for evaluation during 1989 to 1993. Identifying information was used in these records to conduct a telephone survey of the inventors, obtaining 561 usable telephone survey responses for an adjusted response rate of 75%. For background demographics data and tests for sample selection bias, please see Åstebro and Gerchak (2001). Out of the 561 inventions, 50 had been brought to market according to interviews. Three inventors could not recall the entry or exit date, leaving 47 inventions for use in survival analysis. The chance of commercialization is therefore approximately $50/561 = 0.09$. Correcting for sampling plan and conducting sensitivity analysis, the probability of commercialization varies between 0.05 and 0.11 (Åstebro, 1998; Åstebro and Bernhardt, 1999; Åstebro and Gerchak, 2001). This rate differs from Griffin (1997), who found the probability of commercialization of new ideas to be approximately 0.25 among Product Development Management Association (PDMA) member firms. Mansfield et al. (1971) arrived at a similar estimate for large established firms. The 47 inventions reaching the market represent the sample on which the survival regression analysis was conducted. Many of the inventions reviewed by the CIC are consumer oriented (47%). Other fall into a variety of other categories, including high-technology (6%) and industrial equipment (6%). The sampled record for each invention included ratings for each of the 37 early-stage characteristics (Appendix A) on which analysts at the IAP evaluate product ideas. Data on the independent variables were consequently collected before outcomes were observed, and independently of this study. Therefore, methods or hindsight bias are avoided. Evaluations of the 37 criteria by the IAP experts were made on a three-point linguistic scale (''acceptable,'' ''borderline,'' and ''critical weakness''). These were transformed into numeric values with equal distance between the scores.

To alleviate concerns about interrater reliability, it is noted that the IAP employed the same chief evaluator during the sampling period. Further, all IAP analysts were trained in the procedure by the chief evaluator. The initial training took two days, and close supervision was required for an additional fortnight. Baker and Albaum (1986) tested the reliability of the instrument across 86 judges and six products and founnd Cronbach's alphas ranging from 0.84 to 0.96.

Results

Consistent with the recommendation in Henard and Szymanski (2001) to use multi-item scales in product development research, the first task of the present study was to organize the set of 37 criteria into subsets that could form composite variables, using empirical methods.

Rationale for Using an Empirical Approach to Form Composite Variables

The IAP's list of 37 criteria was developed with several purposes in mind. One is to provide specific feedback to inventors about any shortcomings of products (e.g., technical, usability) in case these could be addressed by additional development efforts. Another is to assess overall likelihood of product success, which might lead either to dissuading inventors with a poor prognosis or to enhancing the prospect of continuing product development and to obtaining funding for inventions judged very favorably.

While the original criteria were derived based on scientific research, the a priori grouping of the criteria by the IAP appears to be somewhat arbitrary. For example, although the 37 criteria are organized into four overarching categories (technical, production, market, and risk factors), some criteria in different categories seem likely to covary substantially (e.g., tooling cost required to meet expected demand—classified as a "production" factor—and whether the likely size of required investment was likely to be obtainable—a "risk" factor). Also, within each category there appear to be quite separate subcategories, or "constructs" in the language of scientific research. For example, risk factors included legal concerns (e.g., product liability potential), dependence of the product on other products/systems, and direct financial risks.

Consequently, it was necessary to identify and to use an exploratory method of data analysis that would distinguish research-appropriate constructs and their indicators in these data. In particular, this study sought to identify homogeneous subsets of criteria that could be combined to form readily interpretable composite variables. In addition, it was necessary that these combinations be distinct from one another, to reduce the problems that arise in predictive analyses when predictors are overlapping.

Implementing a Method of Construct Identification

Gorsuch (1983) noted that some investigators (e.g., Cureton, Cureton, and Durfee, 1970) have combined factor analysis with cluster analysis to improve detection of constructs when measures have not been refined a priori to provide simple structure. In this two-stage procedure, correlations among variables ultimately determine the inferred structure and scheme for combining measured variables into composite variables. However, by first representing correlations in terms of orthogonal factors[1] (in a matrix of common factor loadings), it becomes possible to calculate a matrix of the distances of measured variables from one another in the orthogonal-dimension space described by the factors. Such a matrix of distances is necessary for the second stage of analysis—cluster analysis.

In the clustering stage, measured variables (say, X1 and X2) are placed with one another in a cluster to the extent that they correlate with variables in a similar pattern (e.g., X1 and X2 both correlate highly with X3 and X4 but not with X5 and X6). As noted by Tryon and Bailey (1970), this basis for forming composite variables[2] corresponds very well with the concept of a construct, for example, as discussed in Campbell and Fiske (1959).

Interpreting and Using Findings to Form Primary Composite Variables

Findings from the cluster analysis, which was performed on all 561 observations, are presented as the "dendrogram" in Figure 1. The dendrogram is the pattern of lines connecting the 37 criteria to one another in a branching, tree-like structure. When measured variables appear near one another in the list in the left-hand part of the figure, and when they are seen to be connected most directly by lines in the right-hand part, they are the ones most similar to one another in how they correlated with other variables. Such similar variables thus are inferred to be co-indicators of a construct.

It should be emphasized here that this branching structure is fully empirical in nature; it is not a representation of how the present authors thought the items should join. Judgment came into play in labeling the divisions implied by branching structure. For the present study's primary scheme for forming composites, the structure was divided into the 14 clusters indicated in the column of Figure 1 that gives each measured variable's cluster number (labeled as "Clu. Num."). One consideration in arriving at 14 clusters was the fact that it takes approximately 14 groupings to divide 37 measured variables into groups with two or three indicators—and the wide range of content of the 37 variables implies there can only be a few indicators of each construct. In addition, although not definitive, a chi-square test of residual correlations after factoring pointed to the existence of 14 factors.

Most importantly, the 14 clusters are quite interpretable. For example, cluster 1 is concerned with anticipated profit for the producer of the product. Cluster 2 involves price but also investment costs for the producer, which is a complication this research will address. As a final example, cluster 3 concerns

[1] This study used principal axis factoring as the method of factor extraction, retaining the 10 factors with eigenvalues above 1. No rotation of factors was used because the clustering method yields invariant findings as long as factors remain orthogonal. Input data were the 37 ratings on all inventions evaluated by the IAP in the study period, including those not brought to market (thus allowing a favorable ratio of cases to variables and maintaining relevant variability in the data).

[2] Hierarchical clustering by the diameter (or furthest neighbor) method was performed on a proximity matrix calculated among variables (rows) in the factor matrix. The proximity of any variable pair (x, y) was a cosine calculated as $\sum_i (x_i y_i) \Big/ \sqrt{\left(\sum_i x_i^2\right)\left(\sum_i y_i^2\right)}$.

Rating Variable Name Description	Var. Num.	Clu. Num.
Payback Period (Is investment recoverable soon?)	36	1
Profitability (This investment superior to alternatives?)	37	1
Potential Sales (Likely volume justifies project?)	35	1
Tooling Cost (required to meet expected demand)	8	2
Size of Investment (Is necessary total likely to be obtainable?)	34	2
Price (Advantage over competitors?)	24	2
Promotion Cost (In line with expected earnings?)	28	3
Distribution (How difficult to develop/access channels?)	29	3
Market Research (Effort required to define product & price)	27	3
Visibility (How evident are its advantages to customer?)	19	4
Appearance (conveys a message of desirable qualities?)	20	4
Compatibility (w/ current attitudes and ways of doing things?)	17	4
Durability (Will this innovation endure "long usage"?)	22	4
Service (Will require less costly servicing than alternatives?)	23	4
Learning (How easy for customer to learn correct use?)	18	4
Technology of Production (available to produce the invention?)	7	5
Cost of Production (Reasonable production cost possible?)	9	5
Technical Feasibility (Technical solution sound & complete?)	1	6
Research & Development (Amount remaining to market?)	3	6
Functional Performance (Achieves intended purpose?)	2	6
Development Risk (Amt. of uncertainty to become market-ready)	31	6
Comparative Functionality (Better than alternatives?)	21	7
Societal Benefits (Is innov. of general benefit to society?)	16	8
Legality (Does invention meet laws, etc.; avoid prod. liability?)	30	8
Demand Predictability (How possible to predict sales closely?)	14	9
Product Line Potential (to lead to other profitable products/svcs)	15	9
Safety (Potential dangers or bad side effects expected?)	5	10
Environmental Impact (Pollution, litter, resource misuse likely?)	6	10
Technology Significance (Contrib. to technol. or to its application)	4	11
Protection (likely from patent, trade secret, or other means?)	33	11
Trend of Demand (expected to rise remain steady, or fall?)	12	12
Duration of Demand (Demand expected to be "long term"?)	13	12
Potential Market (How large and enduring for all such products?)	11	13
Dependence (on other systems etc., thus no control of sales?)	32	13
Need (Does the innov. solve a problem, fill a need or want?)	10	13
Existing Competition (makes entry difficult and costly?)	25	14
New Competition (likely to threaten market share?)	26	14

Clustering Structure

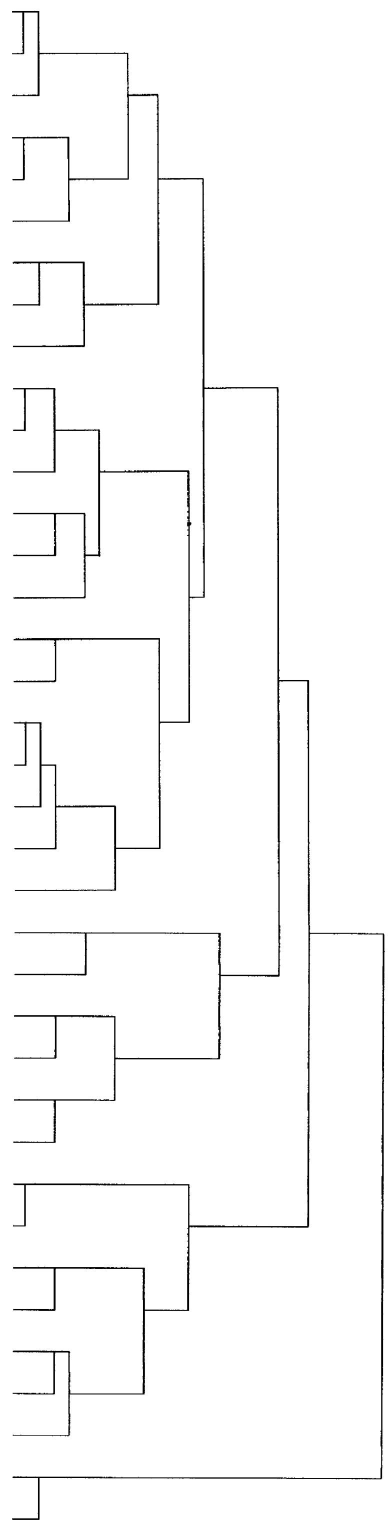

Figure 1. Dendrogram Representation of Findings from Cluster Analysis Concerning Correlations among IAP Criteria for Evaluating Innovations

various marketing and sales costs for the producer. The nature of other clusters will be discussed later in instances where they predict survival.

Thus, a set of 14 composite variables was calculated according to the cluster numbering scheme in Figure 1. For example, the composite corresponding to cluster 1 was formed by averaging ratings on Payback Period, Profitability, and Potential Sales. Table 1 shows the Pearson correlations among the resulting composite variables. None of these correlations is high enough to jeopardize inferences from using these variables in regression.

Regression

Given these potential predictors, the further task is to regress the dependent variable, survival, on the composite variables while controlling for right censoring. Maximum likelihood estimation of a parametric proportional hazard model of the general form was used:

$$h(\boldsymbol{t}_j) = h_o(t)g(\boldsymbol{x}_j),$$

where $h_o(t)$ is the baseline hazard function, parametrized as $h_o(t) = 1$ (the exponential), and $g(\boldsymbol{x}_j)$ is a nonnegative function of the covariates, here specified as $g(\boldsymbol{x}_j) = e^{x_j\beta}$. This study reports unexponentiated coefficients (i.e., the β's) and leaves out reporting the estimate of the baseline hazard, which is uninformative. The likelihood function is further adjusted by adding a branch for those observations that are right censored at time τ, estimating the probability of censoring given survival until time τ. The dependent variable is the probability of failing in each time period, conditional on surviving until that time, and the independent variables (covariates) are the 14 clusters identified in Figure 1. Higher values on the predictor variables indicate more favorable assessments by the IAP. Under the proportional hazard model, a negative regression coefficient means that an increase in the predictor decreases the probability of exit. Thus, significant negative coefficients point to predictors of longer survival.

Findings from this regression analysis are presented in Table 2. Near the bottom of the table is provided a test of overall model fit, a likelihood ratio test yielding a chi-square value of 25.45, which is significant at the 0.05 level. This test is analogous to a multiple d.f. test for overall R^2 in a conventional regression model for continuous outcome data. Thus, this study's test indicates that there is some significant prediction of survival overall from these predictors (despite the relatively small ratio of variables to cases and the resultant risk of overfitting the data). Not shown in the table is the implication of this model of an estimated baseline hazard pointing to a constant probability of exit of 0.09 in each year.

Turning to the coefficients and statistical tests for individual predictor variables, it can be seen first that a significant ($p < .01$) and positive (inverse) effect is obtained for "Entry cost and Price." "Technical product maturity" and "Demand certainty" have negative significant effects ($p < .05$), and "Competition" has a negative and near-significant effect ($p < .10$).

"Entry cost and Price" combines three criteria: "price," "tooling cost," and "size of investment." The positive association between price and exit probability is understandable because a higher price is reflected by a lower (not higher) rating by the IAP. Analysts at the IAP rated lower price as more favorable (higher ratings) as, according to them, it would make the product more attractive to purchasers. However, this research finds that higher price is more favorable to survival. The result lends support to the idea that price is exogenously determined. That is, prices are typically determined by choice of product/industry and are relatively fixed once entering competition (Jovanovic, 1982). This interpretation assumes that the inventors who bring their products to market do, in fact, price their products higher when IAP evaluators indicate that the price would have to be relatively high. That is, it should be kept in mind that this prediction involving price and survival, like all other predictions here, is based on an evaluation before product launch as it predicts later survival.

However, "Entry cost and Price" includes two indicators of the investment cost that contaminate the ability to interpret the effect of price alone. Additional regression analysis (proportional hazard) therefore was conducted where the effect of price is separated from the two measures of investment cost. This regression shows price to have an independent positive and significant coefficient value at 4.29 ($p < .05$), supporting the previous interpretation, while the average score of tooling cost and size of investment also has a positive and significant coefficient value at 3.18 ($p < .05$). A more favorable rating by the IAP of the size of investment, reflecting a lower absolute investment, results in a higher probability of exit. The IAP considers a smaller investment more favorable because an entrepreneur "does not have to take as large a risk." However, in terms of survival a lower

Table 1. Pearson Correlations among Cluster-Based Composite Variables[a]

c1														
c2	0.30													
c3	0.26	0.12												
c4	0.34	0.44	0.23											
c5	0.34	0.31	0.12	0.19										
c6	0.34	0.41	0.29	0.49	0.33									
c7	0.19	0.28	0.10	0.53	0.12	0.27								
c8	0.30	0.17	0.17	0.33	0.14	0.21	0.25							
c9	0.15	0.19	0.14	0.32	−0.01	0.14	0.30	0.27						
c10	0.13	0.29	0.03	0.33	0.14	0.12	0.22	0.19	0.23					
c11	0.46	0.28	0.18	0.38	0.25	0.46	0.20	0.26	0.18	0.20				
c12	0.18	0.24	−0.08	0.27	0.03	0.04	0.25	0.18	0.41	0.24	0.15			
c13	0.36	0.40	0.13	0.47	0.28	0.35	0.31	0.27	0.28	0.41	0.39	0.29		
c14	0.31	0.14	0.10	0.20	0.22	0.25	0.13	0.13	0.07	0.06	0.26	0.11	0.28	
	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14

[a] Figure 1 tells the items that went into forming composites c1 through c14.

Table 2. Regression Results

Cluster Number	Predictor Variable	Coefficient	Standard Error
C1:	Overall Expected Profit	−2.35	(2.10)
C2:	**Entry Cost and Price**	**7.49*****	**(2.48)**
C3:	Marketing and Sales Costs	2.28	(1.57)
C4:	Product Appearance	−2.16	(2.40)
C5:	Manufacturing Costs	0.76	(1.74)
C6:	**Technical Product Maturity**	**−5.30****	**(2.50)**
C7:	Comparative Functionality	−0.14	(1.49)
C8:	Social Regulatory Compliance	1.00	(1.55)
C9:	**Demand Certainty**	**−2.70****	**(1.06)**
C10	Safety and Environmental Impact	0.22	(1.16)
C11:	IP Significance and Protection	1.88	(1.55)
C12	Demand Growth	−1.26	(1.98)
C13	Market Size	1.52	(1.74)
C14	*Competition*	*−2.94**	*(1.84)*
	−2 LOG L	58.15	
	Likelihood Ratio	25.45**	
	Number of cases	47	

* $p<.10$.
** $p<.05$.
*** $p<.01$.

absolute investment reflects a lower entry barrier and therefore a greater probability to exit, which appears to be due to the entry of greater numbers of marginal innovations.

The next composite variable that predicts survival is labeled "Technical product maturity." It consists of the items "technical feasibility," "functional performance," "research and development," and "development risk." High values on these variables at the time of IAP evaluation imply that the invention is in a relatively advanced state of development.

The statistically significant composite variable "Demand Certainty" consists of two criteria: "demand predictability," and the breadth of products and services that the innovation lends itself to—"product line potential." A high rating of demand predictability suggests that the innovation faces stable demand, rather than a highly fluctuating demand. The more stable the estimated future demand, the longer the predicted survival. This result becomes most understandable by assuming stochastic demand and a fixed cost in each period. A high rating on product line potential, on the other hand, suggests that the innovation appears to lend itself to a variety of products or services and that this rating is also associated with greater sales longevity. Again, a simple and analogous probabilistic argument can explain this result. If demand fluctuates from year to year for any given product line, then the greater the number of product lines the lower the probability that a significant drop in demand for a single product line will cause an inventor to discontinue sales of the innovation altogether. That is, greater applicability across a number of products or services provides for risk spreading and reduces the hazard of exit due to random events.

The composite variable "Competition" consists of items describing both competition from established firms and the probability that there will be imitators entering one's market. Its effect is in the predicted direction but is only marginally significant.

Finally, to examine the robustness of results, an accelerated failure time model with an exponential duration distribution also was estimated (not reported). Results are entirely consistent with the

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proportional hazard model, except that "Competition" does not have a robust effect across the two model specifications.[3]

Discussion

It is of interest to learn which characteristics predict, at an early stage, the duration of an innovation's length of sales, because this duration is important to the financial success of new products. New products expected to live longer in the market are expected to return greater profits, all else equal. Past research (Mansfield et al., 1977) indicates that managers can inform their expectations by undertaking systematic evaluations of innovations at an early stage of development.

Here, the duration of sales of new and innovative product projects undertaken by inventors/entrepreneurs is studied. Although their projects are between four to eight times less likely to reach the market compared to new products developed in established organizations (Åstebro, 1998; Griffin, 1997; Mansfield et al., 1971), making generalizability to such products uncertain, we note that commercially and culturally significant innovations often do come from "garage"-based development efforts. Arguably, the original Apple computer is one example (Halliday, 1983). The pull-top beverage can is another (Dalton, 2003); the modern brassiere, yet another (Levins, 1996).

The present study's results are not dissimilar to what would be expected from a study of the survival of new products developed by established organizations. New products that are technically and functionally sound (signaled here by the technical product maturity predictor), that compete in industries with higher price (generating greater profits), and that face less intense competition are more likely to survive longer. The results are analogous to those of the meta-analysis by Henard and Szymanski (2001) in that the dimensions of product advantage and competitive response appear in both. The differences may be more interesting and are discussed further as primarily a function of the focus on new product survival rather than due to the focus on independent inventors and expert ratings.

[3] This research also experimented with other survival functions that did not constrain the hazard to be constant over time. Additional parameters reflecting nonconstant hazards over time were not significant, supporting the use of the exponential duration distribution. Detailed results are available from the corresponding author on request. Also see Gerchak and Åstebro (2000).

If the entrepreneur has entered a market partly unaware that competitive conditions are as severe as they appear after entry, those who entered paying a lower fixed entry cost and facing higher demand uncertainty would be more likely to exit. This interpretation of the present study's findings meshes with Jovanovic's (1982) theory, which assumes that entrepreneurs have only a vague idea about industry competitive conditions when entering and learn most about it after entry. It is to be noted that lower cost of entry is likely to induce higher probability of entry, while, as shown, it also induces a higher probability of exit. The present study's idea of focusing on a single well-defined outcome variable, the length of survival, is shown to bear fruit. If one had examined the impact on "overall success"—mixing up the two outcomes—the differential effects of the investment cost on entry and exit probabilities might have washed out. It is further not clear that demand uncertainty and product line potential play any role in determining commercialization success. The present article, however, showed these variables both theoretically and empirically to determine the survival of innovations.

The present work also finds that higher "technical product maturity" leads to longer survival duration. This study's interpretation is that development shortcomings carry through beyond product launch, such that products launched before major development issues have been worked out encounter various difficulties implied in the items of this cluster (cf. Jovanovic, 1982). These difficulties include inadequate "functional performance" for the customer and a potentially wide range of problems (e.g., product reliability, manufacturability) implied in the remaining items in this cluster. The concept of product quality (e.g., Garvin, 1988) captures many of these risks for products that are less developed.

This study's focus on survival contributes much needed conceptual and managerial clarity to the study of new product development. It was found that for the typical invention the probability of exiting the market in each year is approximately 0.09. Three variables were found to significantly shift this mean probability of exit up or down, and these three are possible to assess at an early stage of the inventions' development. With estimates of these variables plugged in to the described survival model, one can compute the expected survival time for a specific invention and can use this and other information to compute the expected return of an invention. Gerchak and Åstebro (2000) provided formulas into which to plug numbers.

The basic task in this research was to learn about innovation survival from secondary analysis of an unusual and promising database. However, it should be recognized that the data were not originally intended for factor/cluster analysis and formal or statistical predictive analysis. On the one hand, the small number of indicators for each composite variable was far from ideal for power or stability of prediction. On the other hand, three of these composite variables proved to be significant predictors of survival. In addition, there was substantial collinearity in the raw data, suggesting the usefulness of cluster analysis to combine variables to reduce collinearity. Moreover, the analysis resulted in composite variables that did not deviate a great deal from the conceptual schema of the IAP and that were quite interpretable. In sum, this research judged the predictive variables to be good enough on the whole, although better measures certainly should be sought for future research.

A potentially problematic issue is that the purpose of the early stage evaluation is to provide the potential entrepreneur with advice on whether and how to continue R&D efforts, rather than predicting the probability of survival. In other words, the ratings for the explanatory variables for a specific invention may not stay the same after the evaluation if the inventor/entrepreneur makes efforts to improve some of the characteristics according to the advice provided by the IAP. If entrepreneurs work toward correcting problems identified by the IAP and then succeed in launching products then the explanatory power of the original criteria are biased downward. In addition, the sample used for predicting survival was fairly small (47 observations), leading to low statistical power. Finally, one should notice that the evaluation was done well ahead of market launch.

Given these limitations, it is impressive that several IAP criteria did predict survival individually and that the set of criteria collectively provided statistically significant prediction of survival (according to the likelihood ratio test, as reported in Table 2). Holding the pattern of findings at arm's length, distinct kinds of composite variables can be seen that did not provide any significant prediction and other kinds that sometimes did. A seemingly key variable that did not provide prediction was one involving profit quite directly (cluster 1). This variable was of a summary or integrative–judgmental nature, and its failure to predict is consistent with literature concerning superiority of statistical over subjective integration and prediction (Dawes, Faust, and Meehl, 1989). For predictive purposes, at least, it appears that it is best to use component or attribute ratings that go into such summary judgments, instead of the summary judgments themselves. Another kind of variable that did not predict survival concerned risks such as product liability or windfalls as when a product spawns unusual societal benefit. Although variables of this kind may affect survival, the present work suspects that the rate is too low for detection of effects in a relatively small sample like the present one.

Many would-be entrepreneurs probably will find most surprising the lack of findings for some of the composite variables that concern market factors, particularly need, potential market, visibility of product advantages, and comparative functionality. It is reiterated that this result might be due to the present research's focus on product survival. The variables may still be determinants of the probability of entry, and/or the yearly profit rate conditional on entry. [See Åstebro (2004) for an analysis of determinants of the probability of entry.] Evidently, "building a better mousetrap" in these respects is not enough for product survival. The innovation should (1) face stable demand; (2) be saleable at a price sufficient for profit; and (3) undergo development before product launch to an extent likely to promote product quality on a variety of dimensions. These are, of course, business considerations of the kind that the IAP was designed to bring to inventors' attention.

What can other researchers learn from this study for future research? It is certainly possible and of interest to replicate this study's design using other samples. What seem to be critical ingredients are (1) a large sample of projects; (2) project screening criteria measured at an early stage; and (3) a clear outcome variable. Future researchers and early-stage evaluators also may benefit from considering the empirical scheme (Figure 1) derived for this study, which groups and distinguishes many important product evaluation variables. The previous dominant research design of post-outcome mail surveys with fuzzy or no definition of the outcome variable should be avoided.

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Appendix A. Variables Assessed by the IAP

#	Variable Name	Description
	Technical Factors	
1	Technical Feasibility	Is the technical solution sound and complete?
2	Functional Performance	Will the innovation effectively achieve the intended purpose?
3	Research and Development	How great a burden is the remaining research and development required to bring the innovation to a marketable stage?
4	Technology Significance	How significant a contribution to technology or to its application is proposed?
5	Safety	Are potential dangers or undesirable side effects expected?
6	Environmental Impact	Will the innovation lead to pollution, litter, misuse of natural resources, or the like?
	Production Factors	
7	Technology of Production	Are the technology and skills required to produce the invention available?
8	Tooling Cost	How great a burden is the cost of production tooling required to meet the expected demand?
9	Cost of Production	Does production at a reasonable cost level appear possible?
	Market Factors	
	Demand	
10	Need	Does the innovation solve a problem, fill a need or satisfy a want for the customer?
11	Potential Market	How large and how enduring is the total market for all products serving this function?
12	Trend of Demand	Will the demand for such an innovation be expected to rise, remain steady, or fall in the lifetime of this idea?
13	Duration of Demand	Is the demand for the innovation expected to be "long term"?
14	Demand Predictability	How closely will it be possible to predict sales?
15	Product Line Potential	Can the innovation lead to other profitable products or services?
	Acceptability	
16	Societal Benefits	Will the innovation be of general benefit to society?
17	Compatibility	Is the innovation compatible with current attitudes and ways of doing things?
18	Learning	How easily can the customer learn the correct use of the innovation?
19	Visibility	How evident are the advantages of the innovation to the prospective customer?
20	Appearance	Does the appearance of the innovation convey a message of desirable qualities?
21	Comparative Functionality	Does this innovation work better than the alternatives? or fulfill a function not now provided?
22	Durability	Will this innovation endure "long usage"?
23	Service	Will this innovation require less servicing or less costly servicing than alternatives?
	Competition	
24	Price	Does this innovation have a price advantage over its competitors?
25	Existing Competition	Does this innovation already face competition in the marketplace that will make its entry difficult and costly?
26	New Competition	Is this innovation likely to face new competition in the marketplace from other innovations that must be expected to threaten its market share?
	Effort	
27	Marketing Research	How great an effort will be required to define the product and price that the final market will find acceptable?

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Appendix A (Cont'd.)

#	Variable Name	Description
28	Promotion Cost	Is the cost and effort of promotion to achieve market acceptance of the innovation in line with expected earnings?
29	Distribution	How difficult will it be to develop or access distribution channels for the innovation?
	Risk Factors	
30	Legality	Does the invention meet the requirements of applicable laws, regulations, and product standards and avoid exposure to product liability?
31	Development Risk	What degree of uncertainty is associated with complete successful development from the present condition of the innovation to the market ready state?
32	Dependence	To what degree does this innovation lose control of its market and sales due to its dependence on other products, processes, systems, or services?
33	Protection	Is it likely that worthwhile commercial protection will be obtainable for this innovation through patents, trade secrets, or other means?
34	Size of Investment	Is the total investment required for the project likely to be obtainable?
35	Potential Sales	Is the sales volume for this particular innovation likely to be sufficient to justify initiating the project?
36	Payback Period	Will the initial investment be recovered in the early life of the innovation?
37	Profitability	Will the expected revenue from the innovation provide more profits than other investment opportunities?