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Product innovation is increasingly valued as a key component of the sustainable success of a business's operations. As a result, there has been a noticeable increase in the number of studies directed at explicating the drivers of new product success. To help managers and researchers synthesize this growing body of evidence, the authors conduct a meta-analysis of the new product performance literature. Of the 24 predictors of new product performance investigated, product advantage, market potential, meeting customer needs, predevelopment task proficiencies, and dedicated resources, on average, have the most significant impact on new product performance. The authors also find that the predictor–performance relationships can vary by measurement factor (e.g., the use of multi-item scales, subjective versus objective measures of performance, senior versus project management reporting, time elapsed since product introduction) or contextual factor (e.g., services versus goods, Asian versus North American markets, competition in high-technology versus low-technology markets). They discuss the implications of these findings and offer directions for further research.

Why Some New Products Are More Successful Than Others

Academic researchers have responded to the growing managerial emphasis on product innovation with increased studies that document the antecedents to new product success. Whereas Montoya-Weiss and Calantone (1994) found 18 causal studies (i.e., using correlational, regression, path, or structural equation analyses) on new product performance when conducting their review, a review of the current literature reveals at least 60 empirical studies that document the statistical relationship between new product performance and its proposed antecedents. This increased amount of research in turn has provided the need and means for a meta-analysis of current empirical findings. The need for a meta-analysis is also heightened by the great differences in the direction, statistical significance, and magnitude of the new product performance effects for the same predictor variable across the reported models (see Montoya-Weiss and Calantone 1994). More important, these disparate findings complicate managers' and academic researchers' efforts to develop a clear and comprehensive understanding of why some new products succeed and others fail.

The purpose of this study is to conduct and present insights from a meta-analysis of the evidence on the determinants of new product performance. The insights that are generated through this quantitative synthesis of the literature are likely to be valued by managers and academics whose job responsibilities and research interests focus on the marketplace performance of new product initiatives. We present this meta-analysis of the new product performance literature with these objectives in mind.

DATABASE DEVELOPMENT

When we developed the database for the meta-analysis, our efforts focused on identifying the population of studies on new product performance. To identify these studies, we conducted keyword searches of electronic databases (ABI/Inform, UMI ProQuest, Ovid, and WILS) using such words as "product innovation," "new products," "pioneering products," and so forth. We also searched the citations found in identified studies and performed manual searches of leading marketing and management journals in which articles on product innovation and new product performance are most likely published (*Academy of Management Journal, Journal of the Academy of Marketing Science, Journal of Marketing,*

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Journal of Marketing Research, *Journal of Product Innovation Management*, *Management Science*, and *Marketing Science*). In addition, we wrote to more than 200 authors of conceptual and empirical studies on product innovation asking them for working papers and forthcoming articles on new product performance. We posted a similar request on the electronic list server for marketing academics (ELMAR, n = 2530 subscribers).

In total, 60 studies that reported one or more antecedents to new product success were identified through these procedures when the search process was concluded in January 1999. It also became clear that the correlation was the most common metric reported in these studies, or it represented the metric to which many of the noncorrelations could be converted (see Glass, McGaw, and Smith 1981). As a final step in the process, we wrote to the authors of studies that did not report correlations or related data and asked them for their respective correlation matrix. Through these collective procedures, we ultimately obtained correlations for 41 of the 60 studies on product innovation (35 published and 6 unpublished studies).[1] The 41 studies yielded 798 correlations that we coded into our database.

The emphasis in the coding of the data and analysis of the correlations is on the model-level correlations (an eventual averaging of reported correlations across all models and all studies to arrive at an estimate of the central tendency of the predictor–criterion relationship, such that n is the number of correlations) rather than the study-level correlations (an initial averaging of the correlations reported within a study followed by a further averaging of the respective mean correlations across studies; n equals the number of studies). A model-level analysis is consistent with the approach advocated by Glass, McGaw, and Smith (1981) and the approach used in previously published meta-analyses (e.g., Assmus, Farley, and Lehmann 1984; Churchill et al. 1985; Sultan, Farley, and Lehmann 1990; Tellis 1988).

A focus on the individual correlations reported across all models is also grounded in several methodological considerations. For example, the proposed moderators in this analysis are categorical and often vary across the estimated models within the same study. As such, a model-level analysis is more appropriate for ensuring that all the potential factors that could be accounting for the differences in the estimated relationships are coded and captured in the database (Matt and Cook 1994). Furthermore, we find that the sampling error variances and mean correlations are comparable at the model and study level, which implies that statements of generalizability are appropriate at either level of analysis (Hunter and Schmidt 1990). Finally, the Q test for homogeneity in correlational values is rejected in 85% (57 of 67) of the cases in which multiple correlations ($n \geq 3$) are reported within a study for the same antecedent to performance (see Hèdges and Olkin 1985). This evidence further implies that capturing and analyzing the data at the model level are more appropriate for this meta-analysis because of excessive heterogeneity in the values of the individual correlations.

When coding the correlations, we also took care to refer to the scales reported in the original studies. We undertook this additional step in the coding process so that dissimilar elements would not be combined inappropriately and conceptually similar variables would not be coded separately, as when different authors use slightly different labels to refer to similar constructs. We also coded other measurement and contextual factors that could distinguish the respective predictor and criterion factors and analyzed these elements for their moderating influences later in the meta-analysis.[2] Coding errors were mitigated by having an independent, professional auditor and one of the authors independently code all the studies. Coding conformity was achieved in 98.2% of the cases. We rectified the few inconsistencies that occurred through discussions and reference to the coding scheme.

ANTECEDENTS OF NEW PRODUCT PERFORMANCE

A review of the predictor variables coded into the database reveals that 24 antecedents have been reported frequently enough ($n \geq 10$ correlations) as affecting new product performance to permit a meaningful investigation of their effects in a meta-analysis.[3] To organize these variables further, a taxonomy was developed. The taxonomy was grounded in existing frameworks found in the literature (e.g., Cooper and Kleinschmidt 1987; Montoya-Weiss and

[1] A bibliography of the studies included in the meta-analysis is available from the authors. Including 68% of all empirical studies in this review is consistent with the inclusion rates reported in other meta-analyses in marketing by Brown and Peterson (1993; 66%); Brown and Stayman (1992; 72%); Szymanski, Bharadwaj, and Varadarajan (1993; 63%); and Szymanski, Troy, and Bharadwaj (1995; 70%).

[2] Differences in how the respective predictor and outcome variables are specified in the survey instrument were examined as possible explanations for the variance in effect sizes. The mean correlations do not differ ($p > .05$) as a function of whether performance is specified as return on investment (.27), sales (.36), share (.38), or profit (.29). Analysis also shows that more-narrow definitions of the respective predictor variables have little effect on the magnitude of the correlations. Many of the variables are specified and coded consistently across studies (e.g., marketing task proficiency, technological proficiency, launch proficiency). When semantic differences seemed possible and enough data points were available, the mean correlations were compared by subcategory of the respective predictor. This was the case for product innovativeness (radicalness versus original, novel versus newness to customer), likelihood of competitive response (previous competitive response indicative of future response versus intensity of competitive actions), and structured approach (structured approach to the new product initiative versus well-specified project roles and schedules). The difference in mean correlations was not significant for product innovativeness ($p = .45$) or competitive response ($p = .18$). Although the difference in means for structured approach was significant at a bivariate level ($p = .03$), it was not significant at a multivariate level ($p = .79$ when we included the element in our ANOVA in Equation 2). Finally, an analysis of year of publication indicated that it too was not a significant moderator of the reported effect sizes. Year of publication was not significantly correlated with the size of the reported new product performance correlations ($r = -.01$, $p > .05$).

[3] Restricting the investigation to predictors that had ten or more observations resulted in 666 correlations being retained for analysis in the study. These correlations capture the 24 consensual variables that have been examined as predictors of new product performance from among the 58 variables that have ever been specified as affecting new product performance in the studies we reviewed. A complete listing of coded factors that had fewer than ten observations is available from the authors. Because of the care taken to ensure that variables were assigned to their proper categories, this list of variables contains elements for which insufficient information was available from the studies to combine the elements confidently into another predictor category.

Table 1
PREDICTORS OF NEW PRODUCT PERFORMANCE

Predictor	*Definition*
Product Characteristics	
Product advantage	Superiority and/or differentiation over competitive offerings
Product meets customer needs	Extent to which product is perceived as satisfying desires/needs of the customer
Product price	Perceived price–performance congruency (i.e., value)
Product technological sophistication	Perceived technological sophistication (i.e., high-tech, low-tech) of the product
Product innovativeness	Perceived newness/originality/uniqueness/radicalness of the product
Firm Strategy Characteristics	
Marketing synergy	Congruency between the existing marketing skills of the firm and the marketing skills needed to execute a new product initiative successfully
Technological synergy	Congruency between the existing technological skills of the firm and the technological skills needed to execute a new product initiative successfully
Order of entry	Timing of marketplace entry with a product/service
Dedicated human resources	Focused commitment of personnel resources to a new product initiative
Dedicated R&D resources	Focused commitment of R&D resources to a new product initiative
Firm Process Characteristics	
Structured approach	Employment of formalized product development procedures
Predevelopment task proficiency	Proficiency with which a firm executes the prelaunch activities (e.g., idea generation/screening, market research, financial analyses)
Marketing task proficiency	Proficiency with which a firm conducts its marketing activities
Technological proficiency	Proficiency of a firm's use of technology in a new product initiative
Launch proficiency	Proficiency with which a firm launches the product/service
Reduced cycle time	Reduction in the concept-to-introduction time line (i.e., time to market)
Market orientation	Degree of firm orientation to its internal, competitor, and customer environments
Customer input	Incorporation of customer specifications into a new product initiative
Cross-functional integration	Degree of multiple-department participation in a new product initiative
Cross-functional communication	Level of communication among departments in a new product initiative
Senior management support	Degree of senior management support for a new product initiative
Marketplace Characteristics	
Likelihood of competitive response	Degree/likelihood of competitive response to a new product introduction
Competitive response intensity	Degree, intensity, or level of competitive response to a new product introduction (also referred to in the literature as market turbulence)
Market potential	Anticipated growth in customers/customer demand in the marketplace

Notes: This classification schema is not offered as definitive but is presented as a reasonable schema that has pedagogical value and intuitive appeal. The possibility that other schemas can be developed that possess or display similar traits is acknowledged and discussed elsewhere in the study.

Calantone 1994).[4] Three product innovation researchers also reviewed the final taxonomy for completeness and appropriateness of classification. They agreed on the four categories—product, strategy, process, and marketplace characteristics—and the placement of specific predictors within each category as being appropriate for classifying the many predictors of new product performance that are examined in our meta-analysis.

Product characteristics encompass both products and services, and the term is used generically to refer to both types of offerings. Product characteristics capture elements pertaining to the offering, such as price, innovativeness, and managers' perceptions of how well the offering meets customers' needs. *Strategy characteristics* refer to a firm's planned actions that have the potential for providing it a competitive advantage in the marketplace separate from any factors associated with the new product development process. These strategic elements include dedicating resources to the new product development initiative, timing market entry, and capitalizing on marketing and technological synergies. *Process characteristics* refer specifically to elements associated with the new product development process and its execution. They encompass department interactions, firm proficiencies, management support, and marketplace orientation and refer to product development initiatives. They also include the development, marketing, and launch of new offerings. Finally, *marketplace characteristics* capture elements that describe the target market and include market potential, competitive activity, and the intensity of that activity (i.e., turbulence) in response to new product introductions.

The complete taxonomy of antecedents to new product performance is presented in Table 1 along with the definitions for each predictor. The direction of the effect typically hypothesized in the original studies and the range of values reported across these studies for each correlate pair are rep-

[4]Our objective was to develop a logical and user-friendly typology for the predictors included in our investigation rather than develop a definitive typology. We recognize that alternative typologies are possible and do exist. Because more predictor variables now characterize the product innovation literature and because our investigation is restricted to the more consensual ones, our taxonomy necessarily resembles rather than perfectly mirrors the previous typologies reported in the literature. For example, Cooper (1979) uses nature of the marketplace, resource bases of the firm, nature of the project, proficiency of process activities, commercial entity, and information acquired. Montoya-Weiss and Calantone (1994) use the following categories: strategic factors, development process factors, market environment factors, and organizational factors. Our framework more closely resembles Montoya-Weiss and Calantone's more recent typology, except that we separate out the many product-related factors that now describe the investigations into new product performance. We also coded organizational factors at a more micro level by placing them into the appropriate strategy or process categories.

Table 2
DESCRIPTIVE STATISTICS FOR THE PREDICTORS OF NEW PRODUCT PERFORMANCE

Predictor	*Classical Hypotheses*	*Range of r Values*	*Number of r Values*	*Number of Studies*	*Cumulative n*
Product Characteristics		–.62, .90	97	35	18,477
Product advantage[a]	+	–.31, .81	44	15	10,261
Product meets customer needs	+	.25, .78	10	4	1941
Product price	+	.11, .64	14	5	3185
Product technological sophistication	+	.20, .90	12	5	1220
Product innovativeness	+	–.62, .81	17	6	1870
Firm Strategy Characteristics		–.73, 1.0	145	33	29,046
Marketing synergy	+	–.02, .71	61	12	15,852
Technological synergy	+	–.73, .68	25	7	9428
Order of entry	+	.10, .94	16	7	1450
Dedicated human resources	+	.00, .70	13	4	1722
Dedicated R&D resources	+	–.19, 1.0	30	3	594
Firm Process Characteristics		–.21, .81	370	95	96,631
Structured approach	+	.00, .43	53	17	6983
Predevelopment task proficiency	+	.19, .76	29	6	12,676
Marketing task proficiency	+	.10, .72	40	6	9000
Technological proficiency	+	.16, .66	14	5	4946
Launch proficiency	+	.04, .66	19	7	5696
Reduced cycle time	+	.00, .44	20	6	2046
Market orientation	+	–.13, .73	60	13	12,437
Customer input	+	–.21, .81	16	10	2331
Cross-functional integration	+	–.05, .58	41	15	7444
Cross-functional communication	+	–.14, .39	58	4	27,859
Senior management support	+	–.07, .46	20	6	5213
Marketplace Characteristics		–.60, .63	54	20	12,496
Likelihood of competitive response	–	–.60, .05	12	4	935
Competitive response intensity	–	–.72, .63	19	10	5608
Market potential	+	.21, .62	23	6	5953

[a]Although this predictor is arguably a second-order factor composed of other product characteristics predictors, it is retained in the analysis because it is frequently captured and reported at this level by researchers.

resentative of the data reported in Table 2. The information in Table 1 therefore provides a reference for interpreting the labels of the individual predictor variables used throughout the study. The information in Table 2 provides a reference for interpreting the direction for the effects that emerge, on average. The data in Table 2 further motivate an investigation of the potential sources for the reported differences in effect sizes.

DIFFERENCES RELATED TO MEASUREMENT METHODS AND RESEARCH CONTEXT

One observation from a review of Table 2 is the wide range in the values of certain correlations that is evidenced in the literature. This naturally raises the question, What accounts for these differences in effect sizes? Previous research in meta-analysis suggests that four broad categories of characteristics often account for systematic differences across correlations (Assmus, Farley, and Lehmann 1984; Sultan, Farley, and Lehmann 1990). They are measurement method, research context, estimation procedure, and model specification. Because our analysis is restricted to bivariate correlations (i.e., the model's estimation procedure is invariant) that are unaffected by model specification (i.e., omitted variable bias is not an issue), subsequent attention focuses on possible measurement method and research context variables as explanations for the differences in the sizes of the correlations. The specific measurement and context factors examined not only are factors that can be coded from the extant studies but also represent elements that have theoretical justification as potential moderating factors (see Table 3). They are elements for which adequate variance exists within a predictor–performance correlate pair (e.g., adequate number of product versus service observations) to permit a meaningful comparison of the correlations by the respective difference factor. The logic in meta-analysis is one of pooling the estimates of association and analyzing the differences in relationship strength according to the elements that can distinguish these effects (Tellis 1988).

In regard to the new product performance literature, the potential distinguishing elements include the following *measurement factors*: multi-item versus single-item performance measure, subjective versus objective performance measure, senior manager versus project manager response data, and short-term versus long-term performance data. They also include the following *contextual factors*: services versus goods, Asian versus North American markets, and high-technology versus low-technology markets. These potential moderators of the respective predictor–performance relationships, as well as the degree to which the effects of the respective predictors generalize across models, are documented through the application of the analyses and their corresponding outcomes, which are discussed next.