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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 ≥ 3) are reported within a study for the same antecedent to performance (see Hedges 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 ≥ 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.

Table 3
OVERVIEW OF THE RATIONALE BEHIND THE RESPECTIVE MODERATOR VARIABLES

Measurement Methods	*Research Context*
Multi-Item Versus Single-Item Performance Measure Multi-item scales (e.g., composite of return on investment, share, and sales) can enhance the ability to assess reliability, ensure a common reference for decision making, and be effective for capturing the broader domain of new product performance (Churchill 1979; Griffin and Page 1996). Using multi-item scales therefore could lead to estimates of association strength that differ from those grounded in data gathered from single-item scales.	*Services Versus Goods* Services are presented as more intangible, less consistent, less separable in production and consumption, and more perishable than goods (Zeithaml, Parasuraman, and Berry 1985). Service evaluations are also presented as being based on different expectations than evaluations of goods and are grounded in processes and outcomes (Gronroos 1982; Zeithaml, Berry, and Parasuraman 1993). These differences could be evidenced in the correlations for new product performance being different for services versus goods.
Subjective Versus Objective Performance Data New product performance has been operationalized through objective data from company records (return on investment, share, sales, or profit) and subjective data from managers (assessments of success versus failure). Whereas objective data derived from standard accounting procedures generally would be considered accurate and bias free, subjective assessments are likely to reflect the biases and imperfect information that characterize human decision making. As a consequence, subjective assessments may overstate or understate the true level of new product performance (Ford, Smith, and Swasy 1990; Nelson 1974), leading to correlations that differ from those grounded in objective data.	*Asia Versus North America* Evidence suggests that the magnitude and statistical significance of certain effects on new product performance can be region specific (Parry and Song 1994; Souder and Song 1997) because of differences in cultural values (e.g., individualism versus collectivism; Hofstede 1980) or differences in new product development processes. Nonaka (1990), for example, describes the Japanese new product development process as highly fluid and iterative, raising the possibility that North American processes may not be similarly fluid or iterative. More important, the possibility of such differences imply that geographic location—Asia versus North America—could moderate estimates of relationship strength in the context of new product performance.
Senior Manager Versus Project Manager Data Whether the data are gathered from project managers or senior managers could make a difference. Project managers often are more familiar with relevant details, monitor the situation more closely, and provide more accurate assessments of product performance. In contrast, senior managers are portrayed as more distant and less involved in the day-to-day activities of new products (Cooper and Kleinschmidt 1995; Griffin and Page 1996; Montoya-Weiss and Calantone 1994). As a result, survey responses and the correlations based on those responses could vary depending on whether senior managers or project managers provided the data.	*High-Technology Versus Low-Technology Markets* High-technology markets have been characterized as more complex, information intensive, turbulent, and uncertain because of rapidly changing and heterogeneous technologies, competitive, and differentially responsive to structural arrangements that can affect the information-processing patterns of buyers (e.g., Capon and Glazer 1987; Glazer 1991; Heide and Weiss 1995). They are also characterized by offerings that are based on significant amounts of scientific and technical know-how (John, Weiss, and Dutta 1999), such as markets served by competitors in the electronics industry (e.g., Maidique and Ziger 1984). These characteristics that define high-technology markets could moderate the effects of a structured approach (greater structure in high-technology markets accompanied by diminished performance), market orientation (gathering and reacting to information being more critical in high-technology markets where more information is available and product cycle time can be shorter), and perhaps other classical predictors of the success of new product offerings.
Short-Term Versus Long-Term Performance Data The correlations could vary depending on whether performance was captured closer to when the product was introduced (less than 36 months) or after more time has elapsed since product introduction (more than 36 months).[a] Product diffusion is grounded in the principle that the first purchases of a new product by a population occur over time (Sultan, Farley, and Lehmann 1990). This implies that the full effects of product, firm strategy, firm process, or marketplace elements on new product performance are likely to be evidenced only after considerable time has elapsed since product introduction. Therefore, the elapsed time since the product was first introduced onto the market could affect estimates of relationship strength.	

[a]Thirty-six months is a point of demarcation often presented in the product innovation literature (e.g., Cooper 1984; de Brentani 1989; Souder and Song 1997). This dichotomous pattern of reporting by authors points to a categorical rather than a continuous specification for time since introduction within the meta-analysis.

FINDINGS FROM THE META-ANALYSIS

Bivariate Tendencies of the New Product Performance Effects

The analysis of the correlations between new product success and its proposed predictors begins with the estimation of the central tendencies of the corrected correlations—that is, the correlations corrected for sampling error (sample size differences) and measurement error (scale reliability differences)—using the classical approach outlined by Hunter and Schmidt (1990).[5] Central tendency and variance statistics for the individual predictors of new product performance are summarized in Table 4. The subsequent discussion of these data emphasizes not only the statistically significant effects but also the relative magnitudes of the effects. Relative effects are emphasized because the firms whose data are captured in the original studies likely represent the efficient frontier of firms (i.e., existing firms that by definition have marketed new products successfully at some time). This implies that firms that have never successfully marketed a new product are underrepresented in the product innovation literature.[6]

[5]The sample size–corrected mean (the mean corrected for unsystematic variance due to differences in sample sizes) is estimated and further corrected for differences in scale reliability (the sample size–weighted mean further corrected for systematic variance due to the variability in the reliability of the measures). The reliability-corrected mean is then the focus in the study because, ceteris paribus, a correlation based on larger samples and estimated from more reliable data is likely to be closer to the population mean. However, reliabilities are not always reported by authors, and therefore the reliability-adjusted mean cannot always be estimated. In such cases, the next best estimate of the population mean, the sample size–weighted mean, is emphasized.

[6]We are grateful to the reviewers for drawing this possibility to our attention.

Table 4

CENTRAL TENDENCY AND VARIANCE STATISTICS FOR THE INDIVIDUAL PREDICTORS OF NEW PRODUCT PERFORMANCE

Predictor	*Simple Mean*[a]	*Sample-Size Adjusted Mean*	*Reliability Adjusted Mean*[b]	*Availability Bias*[c]	*Total Variance*	*Sampling Error Variance*	*Reliability Variation Variance*	*Remaining Variance*[d]
Product Characteristics								
Product advantage	.41*	.46*	.48*	3730	.044	.003	.002	.039 (88.6)
Product meets customer needs	.49*	.50*	n.a.[e]	278	.029	.003	n.a.[e]	.026 (89.7)
Product price	.38*	.35*	n.a.[e]	320	.024	.003	n.a.[e]	.021 (87.5)
Product technological sophistication	.48*	.41*	n.a.[e]	130	.058	.006	n.a.[e]	.052 (89.2)
Product innovativeness	.19	.25*	.24	n.a.	.147	.009	.000	.138 (93.9)
Firm Strategy Characteristics								
Marketing synergy	.29*	.26*	.34*	7196	.021	.003	.001	.017 (81.0)
Technological synergy	.27*	.33*	.31	n.a.	.089	.002	.001	.086 (96.6)
Order of entry	.53*	.42*	n.a.[e]	195	.074	.006	n.a.[e]	.068 (91.9)
Dedicated human resources	.46*	.52*	n.a.[e]	235	.063	.005	n.a.[e]	.058 (92.1)
Dedicated R&D resources	.47*	.45*	n.a.[e]	640	.097	.034	n.a.[e]	.063 (64.9)
Firm Process Characteristics								
Structured approach	.21*	.21*	.25*	4939	.013	.007	.001	.005 (38.5)
Predevelopment task proficiency	.37*	.38*	.46*	3633	.017	.002	.008	.004 (41.2)
Marketing task proficiency	.39*	.40*	.50*	5663	.025	.003	.010	.012 (48.1)
Technological proficiency	.34*	.39*	.43*	999	.012	.002	.005	.005 (41.2)
Launch proficiency	.40*	.41*	.43*	835	.027	.002	.003	.022 (81.5)
Reduced cycle time	.23*	.22*	n.a.[e]	335	.019	.009	n.a.[e]	.010 (52.6)
Market orientation	.31*	.36*	.43	n.a.	.061	.004	.002	.055 (90.2)
Customer input	.33*	.24*	.43	n.a.	.073	.006	.002	.065 (89.0)
Cross-functional integration	.19*	.22*	.23	n.a.	.021	.005	.001	.015 (71.4)
Cross-functional communication	.07*	.06*	.09	n.a.	.009	.002	.000	.007 (77.8)
Senior management support	.22*	.31*	.27*	479	.021	.003	.001	.017 (80.9)
Marketplace Characteristics								
Likelihood of competitive response	–.30*	–.37*	n.a.[e]	176	.035	.011	n.a.[e]	.024 (68.6)
Competitive response intensity	–.07	–.12*	–.08	n.a.	.110	.003	.000	.107 (97.3)
Market potential	.40*	.36*	.54*	3200	.017	.003	.001	.013 (76.5)

*$p \leq .05$.

[a]Simple mean is the correlation across studies unadjusted for sampling error or study artifacts.

[b]Reliability adjustments are based on the distribution of the reliabilities.

[c]Availability bias represents the number of unlocated effects with null results ($r = 0$) that need to exist to bring the adjusted mean down to the just significant level ($p = .05$). in this column, "n.a." refers to the corresponding nonsignificant mean r, which makes it unnecessary to estimate availability bias.

[d]The percentage of total variance remaining is in parentheses.

[e]Predictor or criterion reliability estimates are not reported frequently enough across studies ($n < 2$) to adjust the mean correlation for differences in scale reliabilities.

A review of the data in Table 4 reveals that the effects of several classical elements on new product performance do not generalize across models. It further reveals that only a subset of the statistically significant predictors can be considered dominant drivers of new product performance. This subset of drivers nonetheless spans the full spectrum of predictor categories. Finally, modeling efforts often overemphasize the relatively less dominant drivers of new product performance. Each of these findings is discussed in more detail next.

Significant and nonsignificant drivers. Table 4 shows that the corrected mean correlations for product innovativeness (r = .24), technological synergy (r = .31), market orientation (r = .43), customer input (r = .43), cross-functional integration (r = .23), cross-functional communication (r = .09), and competitive response intensity (r = –.08) are not statistically significant at conventional probability levels (p > .05). Therefore, the cumulative evidence indicates that their effects on performance do not generalize across research models, despite theory and growing research interest that touts the performance merits of emphasizing such factors in the new product performance equation (e.g., Geroski, Machin, and Van Reenen 1993).

The cumulative evidence shows, however, that the effects of market potential, product advantage, marketing task proficiency, and several other classical drivers of new product performance generalize across studies and their models (see Table 4). The corrected mean correlations for 17 of the antecedents are significant above conventional levels of chance ($p \leq .05$), and they bear a directional sign that is consistent with classical perspectives (see Table 2). The high numbers for availability bias reported in Table 2 (i.e., 130 to 7196 additional estimates of zero correlation need to exist in the file drawers of researchers for the mean correlations to be nonsignificant) also indicate that these elements are significant above chance levels.

Dominant drivers of performance. A review of the statistically significant predictors of new product performance reveals that ten of the antecedents can be considered relatively dominant drivers of new product success (mean r > .40). They are market potential (r = .54), dedicated human resources (r = .52), marketing task proficiency (r = .50), product meeting customer needs (r = .50), product advantage (r = .48), predevelopment task proficiency (r = .46), dedicated research and development (R&D) resources (r = .45), technological proficiency (r = .43), launch proficiency (r = .43), order of entry (r = .41), and the technological sophistication of the product (r = .41). These data imply that only a few of the many factors that have been examined repeatedly by researchers thus far demonstrate sufficient ability, on average, to affect performance levels meaningfully.

Breadth of performance drivers. An additional review of these ten predictor variables reveals that they nonetheless represent all four broad-based categories of antecedents to new product success. Three of the predictors are product characteristics (products meeting customer needs, product advantage, and product technological sophistication), two are strategy characteristics (R&D and human resources), four are process characteristics (marketing, predevelopment, technological, and launch proficiencies), and one is a marketplace characteristic (market potential). These findings attest to the intricate nature of the new product performance phenomenon. Although successful performance may depend greatly on relatively few elements, performance is multifaceted, depending on selected elements from each major facet of the new product development and introduction initiative.

Prior emphasis in performance modeling. When only the statistically significant means in Table 4 are considered (e.g., the absolute value of the mean correlation for product advantage with performance), marketplace (r = .46), strategy (r = .43), and product characteristics (r = .43) display greater average effects on new product performance than process characteristics (r = .37). These findings imply that, ceteris paribus, placing more emphasis on marketplace, strategy, and product characteristics than on process characteristics would, on average, be more appropriate for augmenting success levels. These broad categories of predictors also offer greater explanatory and predictive value for modeling the antecedents to new product success. These findings, in turn, raise the question, Which factors have been emphasized the most in previous modeling efforts?

The data reveal that the greatest attention has been directed at capturing process characteristics—that is, the set of elements that the cumulative data indicate have the least impact on new product performance levels (Table 2). Perhaps because process is the primary control that management wields, two to six times as many models have incorporated process characteristics in their equations (n = 370) than strategy (n = 145), product (n = 97), or marketplace characteristics (n = 54). A similar pattern is found when only the predictors displaying statistically significant mean correlations are considered (i.e., the ns are totaled across only the categories of individual predictors that have statistically significant overall means). Process characteristics are captured in 195 models, whereas strategy characteristics are captured in 120 models, product characteristics in 80 models, and marketplace characteristics in just 35 models.

The tendency to emphasize less critical predictors over more dominant predictors of new product success continues when attention shifts to the individual predictor variables. The most frequently modeled predictors (n > 40 modeled effects) are marketing synergy (n = 61), market orientation (n = 60), cross-functional communication (n = 58), structured approach (n = 53), product advantage (n = 44), and marketing task proficiency (n = 40). However, the mean correlations for market orientation and cross-functional communication are not statistically significant, and the mean correlations for marketing synergy (mean r = .34) and structured approach (mean r = .25) are more modest in size. Just two of the dominant drivers of new product success have been modeled relatively frequently: product advantage and marketing task proficiency. Assuming that the respective mean correlations are centered similarly over their population means and the measures of the respective relationships are sufficient, the findings draw attention to a disproportionate modeling emphasis directed at capturing the relatively less important antecedents to new product success. These findings also accent the need to ensure that the more dominant drivers are specified in future performance models.

Multivariate Tendencies of the New Product Performance Effects

In addition to the insights generated from a bivariate analysis of the correlations, a multivariate analysis can reaffirm the bivariate findings and add to understanding by documenting the unique contribution of each of the predictors of new product success. A multivariate regression model of new product performance is therefore estimated. To this end, a matrix of corrected correlations is constructed from the available data and used as input for estimating the following regression model:

$$\text{NPP} = \alpha_1 X_1 + \alpha_2 X_2 + \ldots + \alpha_j X_j + \varepsilon, \quad (1)$$

where NPP is new product performance, X_i are performance predictors, and α_i are the parameter estimates. Because few studies examine or report correlational data on the interrelationships among the antecedents to new product success, the correlation matrix contains data for only a subset of the predictors (see Table 5, Panel A): product advantage, product innovativeness, marketing synergy, technological synergy, structured approach, market orientation, cross-functional integration, and competitive response intensity. The findings from the estimation of Equation 1 are presented in Table 5, Panel B.

Table 5 shows that even the relatively parsimonious model of new product success accounts for a majority of the variance in new product performance, specifically, 59% of the variance (see Equation 1). We also find that product advantage ($\beta = .44$, $p \leq .05$) and technological synergies ($\beta = .42$, $p \leq .05$) have the largest relative effects on new product success rates. This relative order of magnitude and amount of variance captured by the model even hold when the two statistically nonsignificant predictors from the first model are removed and the model is reestimated. Collectively, these data suggest that a reduced model can still account for much of the variance in new product performance.

A further review of the multivariate findings in reference to the previously reported bivariate correlations in which the findings are based (see Table 4) naturally reveals many similarities in the pattern of results across both types of analysis. The mean bivariate correlations for cross-functional integration ($r = .23$, $p \leq .05$) and structured approach ($r = .25$, $p \leq .05$), for example, are relatively small in magnitude, and these factors are not significant in the regression model. Second, the mean correlations for product innovativeness ($r = .23$, $p \leq .05$), market orientation ($r = .43$, $p > .05$), and marketing synergy ($r = .34$, $p \leq .05$) are relatively modest in size or nonsignificant, and their respective regression coefficients are also relatively modest in size ($\beta \leq .30$). Third, product advantage is identified as a dominant predictor of performance in the bivariate analysis ($r = .48$, $p \leq .05$) and emerges as a dominant driver of new product performance in the multivariate analysis ($\beta = .44$, $p \leq .05$) as well. Finally, although the mean correlation for technological synergy is not statistically significant ($r = .31$, $p > .05$), technological synergy is shown to play a practically and statistically significant role in new product success ($\beta = .42$, $p \leq .05$) when the roles of the other elements in the model are factored out. Therefore, when the unique effects of the various drivers of new product performance are investigated, capitalizing on related technologies emerges as a prominent antecedent to new product performance, and offering products that display distinct advantages retains its status as a dominant driver of new product success.

Table 5

CORRELATION MATRIX AND MULTIPLE REGRESSION RESULTS FOR SELECTED PREDICTORS OF NEW PRODUCT PERFORMANCE

A: Correlation Matrix

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1. Product advantage	—								
2. Product innovativeness	.26	—							
3. Marketing synergy	–.12	–.29	—						
4. Technological synergy	–.20	–.27	.44	—					
5. Structured approach	.16	–.07	.36	.22	—				
6. Market orientation	.37	.10	.32	–.06	.45	—			
7. Cross- functional integration	.31	.16	.20	–.06	.36	.50	—		
8. Competitive response intensity	–.08	.03	.04	.16	.01	.09	.04	—	
9. Performance	.48	.24	.34	.31	.25	.43	.23	–.08	—

B: Multiple Regression Results

Predictor	*Standardized Coefficients (β) Model 1*	*Standardized Coefficients (β) Model 2*
Product advantage	.44 (.07)*[a]	.43 (.07)*
Product innovativeness	.30 (.04)*	.29 (.04)*
Marketing synergy	.26 (.11)*	.24 (.11)*
Technological synergy	.42 (.05)*	.41 (.05)*
Structured approach	–.07 (.14)	—
Market orientation	.27 (.07)*	.21 (.06)*
Cross-functional integration	–.08 (.10)	—
Competitive response intensity	–.15 (.04)*	–.15 (.04)*
R^2 (adjusted)	.59 (.57)	.58 (.56)
F (*p*-level)	29.40 (<.01)	31.64 (<.01)
Maximum variance inflation factor	1.83	1.61

[a]Standard errors are in parentheses, and statistical significance is based on the median sample size of 149 on which the individual correlations are based.

Measurement and Context Effects as Explanations of the Differences in Effect Sizes

Preliminary analysis. In addition to identifying the relative effects of each predictor on new product performance, the meta-analysis pursues explanations for why the strength of the respective relationships differs across models. We first highlight a partitioning of total variance into variance attributable to sampling error and to differences in scale reliabilities (see Table 4). This partitioning provides a necessary methodological foundation for pursuing the measurement and contextual factors outlined in Table 3 as sources for the differences in the correlational values. In this regard, if more than 25% of the variance in the correlations remains after the partitioning of variance, a search for other moderating variables is deemed appropriate from the standpoint that any statistically significant moderators that are found are unlikely to be significant because of chance (Hunter and Schmidt 1990). What we find is that 38%–98% of the variance in the new product performance correlations remains after sampling and reliability differences are accounted for (see "Remaining Variance" column in Table 4). These data imply that a further search for explanatory variables is called for.

We executed the search for explanatory variables using dummy-variable regression (or analysis of variance [ANOVA]). A separate ANOVA model was estimated for each of the 24 predictor–performance pairs (Hedges and Olkin 1985; Sultan, Farley, and Lehmann 1990). The objective in estimating these models is one of documenting the effects of the various measurement method and research context variables on resulting estimates of relationship strength. Each estimated model has the following form:

$$r_{NPP,d} = \mu + \varphi_1 Y_1 + \varphi_2 Y_2 + \varphi_3 Y_3 + \varphi_4 Y_4 + \varphi_5 Y_5 + \varphi_6 Y_6 + \varphi_7 Y_7 + \varepsilon, \quad (2)$$

where $r_{NPP,d}$ is the z transformed value of the corrected correlation between new product performance and the respective driver d, φ are parameter estimates, and Y_i are categorical variables specified at two levels. Y_1 is a multi-item versus single-item performance measure, Y_2 is a subjective versus objective performance measure, Y_3 is a senior manager versus project manager respondent, Y_4 is a short-term versus long-term performance measure, Y_5 is service versus product context, Y_6 is Asian versus North American markets, and Y_7 is high-technology versus low-technology markets. The outcomes from this estimation procedure are presented in Table 6.

Measurement effects. The data in Table 6 reveal that the measurement and contextual factors outlined in Table 3 can at times account for a statistically significant portion of the variance in the new product performance relationships. Although eight of the models are not statistically significant and no single factor is statistically significant in more than five of the models, several noteworthy insights emerge from a review of the data. One involves the time frame—whether innovation effects are captured less or more than 36 months after launch. Generally, the sampling time frame matters little in the few cases in which there are enough observations for it to be modeled. However, it is statistically significant in the context of order-of-entry effects ($\beta = -.43$, $p \leq .05$). Order-of-entry effects on new product performance are weaker, on average, when new product performance is a short-term measure. These findings imply that the effects of being first to the market with a new offering are evidenced more fully when considerable time has elapsed since product introduction.

Using subjective versus objective performance measures can also make a difference for estimating performance relationships. The correlations are lower between performance and both reduced cycle time ($\beta = -.74$, $p \leq .05$) and cross-functional integration ($\beta = -.64$, $p \leq .05$) when subjective assessments of performance are used. In contrast, the relationships are higher, on average, in the case of products meeting customer needs ($\beta = 1.68$, $p \leq .05$) and dedicated human resources ($\beta = 1.33$, $p \leq .05$). Although few patterns are evidenced across these data, one that is suggested is that objective performance data yield stronger relationships, on average, with selected process characteristics. This outcome may be capturing the ability to objectively measure cycle time or cross-functional integration so that the nature of the predictor and performance measures is similar. Certainly, more research into this phenomenon is necessary to establish the validity of this or any other explanation put forth in regard to the objectivity of performance levels. However, these findings highlight the need to document the better measure of performance in future studies. How performance is captured can lead to different estimates of relationship strength. Different estimates of relationship strength, in turn, can hold different implications for the content and outcomes of strategic plans.

More research is also called for in regard to the explanations for the outcomes when multi-item versus single-item scales are used for capturing performance. We find that multi-item versus single-item is a significant explanation for the differences in effect sizes across five predictor variables: product advantage ($\beta = -.67$, $p \leq .05$), product meets customer needs ($\beta = -1.41$, $p \leq .05$), marketing synergy ($\beta = .35$, $p \leq .05$), senior management support ($\beta = .63$, $p \leq .05$), and market potential ($\beta = .78$, $p \leq .05$). These data indicate that using multiple items to capture success levels often translates into different measures of association. More important, these measurement differences could lead to different conclusions and different strategies that are manifested in different performance outcomes. Such possibilities, combined with the claims that multi-item measures in general are more reliable and accurate (e.g., Churchill 1979), argue in favor of using multi-item measures of performance when testing models of new product success in the future.

Finally, a review of the data pertaining to measurement effects reveals that senior-level managers place less emphasis on structure ($\beta = -.62$, $p \leq .05$), being first to the market ($\beta = -.58$, $p \leq .05$), and marketing task proficiency ($\beta = -.57$, $p \leq .05$) but place more emphasis on competitive response probabilities ($\beta = .65$, $p \leq .05$) as a key to new product success than do project-level managers. These data imply that it is the project managers who emphasize the preemption of competitors when introducing new products. Senior managers place greater emphasis on searching for markets where the threat of competitive preemption or reaction is relatively small. An intriguing finding is that senior managers, compared with project managers, understate their own contributions to the success of new products. The correlations are significantly lower when senior managers report the effect of senior management support on new product performance ($\beta =$

Table 6
REGRESSION RESULTS FOR COVARIATE ANALYSES

Predictor Variables	Multi- Versus Single-item Measure β (S.E.)[a]	Subjective Versus Objective Criteria β (S.E.)	Senior Versus Project Manager β (S.E.)	Short- Versus Long-Term Performance β (S.E.)	Services Versus Goods β (S.E.)	Asia Versus N. America β (S.E.)	High-Tech Versus Low-Tech β (S.E.)	R^2 (Adjusted)	Maximum VIF
Product characteristics									
Product advantage	−.67 (.36)*	.05 (.22)	−.22 (.48)	n.a.[b]	−.27 (.57)	.00 (.36)	.52 (.79)*	.40 (.31)*	2.11
Product meets customer needs	−1.41 (.46)*	1.68 (.48)*	n.a.[b]	n.a.[b]	n.a.[c]	n.a.[b]	n.a.[b]	.89 (.86)*	3.16
Product price	.38 (.46)	−.28 (.67)	n.a.[c]	n.a.[b]	.64 (.34)*	n.a.[c]	n.a.[b]	.40 (.21)	1.37
Product technological sophistication	−.18 (.42)	.10 (.23)	n.a.[c]	n.a.[b]	n.a.[b]	.80 (.20)*	.72 (.40)*	.91 (.86)*	1.91
Product innovativeness	.02 (.06)	.15 (.51)	n.a.[c]	n.a.[b]	.51 (1.08)	n.a.[c]	−.29 (1.01)	.32 (.09)	1.12
Firm strategy characteristics									
Marketing synergy	.35 (.21)*	−.01 (.17)	.04 (.48)	n.a.[b]	.53 (.20)*	.61 (.20)*	n.a.[b]	.43 (.38)*	2.35
Technological synergy	−.06 (.68)	−.19 (.40)	n.a.[b]	n.a.[b]	.10 (1.89)	n.a.[b]	n.a.[b]	.07 (.00)	1.25
Order of entry	−.31 (.35)	n.a.[c]	−.58 (.25)*	−.43 (.46)*	−.19 (.20)	n.a.[b]	−.40 (.37)*	.89 (.84)*	2.64
Dedicated human resources	n.a.[b]	1.33 (.20)*	n.a.[b]	.12 (.41)	n.a.[c]	n.a.[c]	.61 (.27)*	.95 (.94)*	2.24
Dedicated R&D resources	−.26 (.42)	n.a.[b]	.29 (.44)	n.a.[b]	−.06 (.63)	n.a.[b]	.32 (.53)	.20 (.07)	2.45
Firm Process Characteristics									
Structured approach	−.29 (.17)	−.20 (.16)	−.62 (.21)*	−.11 (.18)	−.46 (.18)*	−.02 (.19)	−.44 (.29)*	.47 (.39)*	3.13
Predevelopment task proficiency	.39 (.71)	.08 (.16)	−.11 (.45)	n.a.[b]	.30 (1.15)	n.a.[c]	n.a.[b]	.12 (.00)	2.07
Marketing task proficiency	.29 (.27)	.19 (.19)	−.57 (.21)*	n.a.[b]	−.01 (.69)	n.a.[c]	n.a.[b]	.47 (.41)*	1.65
Technological proficiency	.53 (.47)	−.52 (.17)*	−.49 (.51)	n.a.[b]	.04 (.86)	n.a.[c]	n.a.[b]	.60 (.43)	2.71
Launch proficiency	−.06 (.33)	.41 (.21)	−.20 (.68)	n.a.[b]	−.08 (.69)	.49 (.76)	n.a.[b]	.55 (.48)*	5.85
Reduced cycle time	−.18 (.71)	−.74 (.16)*	.05 (.78)	.35 (.80)	n.a.[b]	n.a.[b]	.21 (.25)	.70 (.59)*	5.31
Market orientation	.25 (.35)	−.04 (.28)	n.a.[c]	.13 (.75)	−.06 (1.34)	.61 (.29)*	.21 (.72)	.40 (.37)*	1.42
Customer input	.27 (.72)	−.09 (.75)	.56 (.80)	.02 (1.21)	n.a.[c]	.57 (1.04)	.43 (1.11)	.60 (.33)	6.69
Cross-functional integration	−.03 (.30)	−.64 (.17)*	.17 (.26)	n.a.[c]	−.19 (.26)	−.12 (.18)	n.a.[b]	.35 (.25)*	1.47
Cross-functional communication	n.a.[b]	.00 (.90)	n.a.[c]	n.a.[b]	−.52 (.59)*	−.35 (1.06)	n.a.[b]	.16 (.11)*	3.21
Senior management support	.63 (.23)*	−.14 (.10)	−.47 (.37)*	n.a.[b]	.07 (.40)	1.32 (.23)*	n.a.[b]	.86 (.81)*	4.10
Marketplace Characteristics									
Likelihood of competitive response	n.a.[b]	n.a.[c]	.65 (.35)*	n.a.[b]	.17 (.44)	−.75 (.34)*	n.a.[b]	.81 (.74)*	1.87
Competitive response intensity	.02 (.47)	−.27 (.45)	.18(1.25)	n.a.[b]	−.21 (1.37)	−.11 (1.41)	.27 (1.35)	.38 (.07)	8.15
Market potential	.78 (.22)*	−.20 (.13)	.28 (.62)	n.a.[b]	n.a.[b]	.08 (.79)	n.a.[b]	.57 (.47)*	2.48

*Significant at $p < .05$.

[a]The covariate factor listed first represents the 1 dummy code; the second measure represents 0.

[b]There is an insufficient number of observations in one of the comparison groups to permit meaningful analysis.

[c]A variable was removed from the equation because of excessively inflated multicollinearity levels.

Notes: S.E. = standard error.

–.47, $p \leq .05$). Either senior managers are modest in the assessment of their ability to create an atmosphere in which new products thrive, or they are unaware of the value of their support to the success of new product initiatives. Either way, project managers perceive the support they receive from senior managers as more vital to the success of new product introductions than do the senior managers responsible for providing this support.

Contextual effects. In addition to measurement effects, the findings in Table 6 indicate that geographic region (Asia versus North America), type of offering (services versus goods) and nature of the market (high-technology versus low-technology markets) can account for some of the variance in the predictor–performance relationships. The regression findings here point to several cases in which performance correlations differ by geographic region. The effects on performance of technological sophistication ($\beta = .80$, $p \leq .05$), marketing synergies ($\beta = .61$, $p \leq .05$), market orientation ($\beta = .61$, $p \leq .05$), and senior management support ($\beta = 1.32$, $p \leq .05$) are all greater in an Asian context, particularly when the threat of competitive reactions is also low ($\beta = -.75$, $p \leq .05$). These findings imply not only that producing and selling new offerings is not the same across Asia and North America but also that successful performance in Asian markets accrues to firms that display more marketing savvy and top management support. Success also accrues to firms that sell in carefully chosen, high-technology markets (i.e., markets where the threat of competitive reactions is minimal).

With regard to the type of offering, services versus goods, the findings show that the predictor–performance relationship is stronger in a service context when the predictor is marketing synergy ($\beta = .53$, $p \leq .05$). However, the relationship is weaker when the predictors are structured approach ($\beta = -.46$, $p \leq .05$) and cross-functional communication ($\beta = -.52$, $p \leq .05$). These findings provide the initial documentation indicating that marketing synergies are more important in a services rather than goods context. These findings may reflect the greater need to communicate further the intangibles that characterize services. They may also reflect the greater need to capitalize on associated knowledge to portray a more complete picture of the service (e.g., capitalizing on brand-name recognition, other service offerings, or other derivatives from brand equity). The data further imply that less structure (i.e., the absence of a structured approach and the absence of the structural impediments that are implied in greater cross-functional communication) has a positive effect on the success levels achieved by new services. This may be because services are more heterogeneous to begin with (Zeithaml, Parasuraman, and Berry 1985) and necessitate less structure so that the new services can be easily customized to match consumer needs.

Similarly, we find that less structure is important ($\beta = -.44$, $p \leq .05$) to the success of new products in markets that are traditionally more turbulent and more uncertain because of heterogeneous and rapidly changing technologies (Glazer 1991). Participants' general lack of relevant experience with new technologies (i.e., a greater probability of making mistakes) and the rapid pace at which technologies become obsolete (i.e., the relatively short time between entry and availability of a superior competitive offering) may also explain why being first to the market is not necessarily a performance advantage for selling new products in high-technology markets ($\beta = -.40$, $p \leq .05$). What is manifested in superior performance is the dedication of personnel to the new product initiative ($\beta = .61$, $p \leq .05$), the offering of products consistent with the general nature of the market (i.e., selling technologically sophisticated products in high-technology markets; $\beta = .72$, $p \leq .05$), and the sale of products that have a distinct competitive advantage ($\beta = .52$, $p \leq .05$). These and other findings are discussed next along with study limitations and directions for future study.

DISCUSSION

The goals of a meta-analysis are to present substantive information about the net effects that characterize a body of research, provide insights into methodological issues, and offer suggestions for further research on the basis of what is known and what remains to be learned (Assmus, Farley, and Lehmann 1984). Thus, a meta-analysis provides a rigorous alternative to a casual, narrative discussion of a rapidly expanding research literature (Wolf 1986). From our review of the empirical literature, we offer insights into the variety of evidence and the multitude of factors that have been reported in the quest to identify the key drivers of new product success. The empirical evidence supports conventional wisdom regarding directionality and statistical significance for several classical variables. We further document the magnitude of the relationships that can be expected, on average, and the conditions under which relatively larger versus smaller performance effects can be expected. The findings simultaneously cast doubt over the performance impact of certain predictors and raise new questions for managers and researchers to address. Several of these effects have already been discussed and are not reiterated here in favor of a discussion that focuses on additional findings and implications; specifically, the relevance of the findings for functional diversity in new product development teams, principles of organizational and strategic alignment, and managerial perceptions and business performance. Functional diversity has been an area of directed research attention in the product innovation literature (see Table 2) and is one in which further observations and insights can be brought to light through the meta-analysis. Issues surrounding alignment and managerial perceptions, in contrast, have not been subjected to much examination or discussion in the context of new products, but again, the meta-analysis can offer several unique insights of relevance to managerial practice and further research.

Functional Diversity

As the use of teams or work groups for the new product initiatives becomes prevalent, questions surrounding the composition of teams for maximizing new product success naturally arise (see Donellon 1993; Norrgren and Schaller 1999). It is relevant to ask, Should team members be from the same functional specialty, or should the team have members from different functional backgrounds? In theory, a greater variety of specialties could bring with it a broader base of knowledge for both managing the new product initiative and identifying and generating new product ideas. Aiken, Bacharach, and French (1980), for example, document a positive relationship between number of occupational specialties and rate of innovation, and King and

Anderson (1990) document a positive relationship between the diversity of team members and creativity.

Although greater diversity in functional specialty may indeed be related to the rate of innovation that results from the generation of new product ideas, the cumulative evidence indicates that elements of functional diversity are not directly related to new product performance per se. In this regard, we find that cross-functional issues and new product performance are not significantly correlated, on average. This is true for both cross-functional integration (mean r = .23, $p > .05$) and cross-functional communication (mean r = .09, $p > .05$). We further find that cross-functional communication effects are moderated by whether services or products are the focus and that cross-functional integration effects are moderated by the nature of the performance data (subjective versus objective). Together, these findings bring into question the blanket need for functional diversity in the context of improving overall new product performance. Although functional diversity can play a role in the tasks that lead up to new product performance (e.g., idea generation) and can be effective for improving performance in limited situations, integration of more functional areas into the new product initiative and heightened communication across these areas may not always represent a productive approach for directly improving the success of new products. Rather, integration in the selected contexts and under the selected conditions outlined may be more advisable.

Strategic Alignment

The findings from the meta-analysis also lend credence to the notion that strategic fit and product performance are related. The literature in both strategic management and organizational theory points to the potential increase in performance that can occur when businesses align themselves to their environment (e.g., Bourgeois 1985; Burns and Stalker 1961). Our analysis of contextual effects in the context of new product performance echoes these theoretical perspectives. We find that a matching of the product, strategies, and processes to the environmental context (see the "Contextual Factors" columns in Table 6) can be important for augmenting new product performance in the sale of goods and services in high-technology markets. For example, the moderator analysis reveals that delaying entry, having less structure, having more personnel, and selling more sophisticated products that have an advantage over other offerings are of greater importance to the success of new products that are targeted to high-technology markets. In other words, properly aligning these elements to the product–service context as well as the technological level of the marketplace can be important for ensuring that new product performance levels are optimized.

The data in Table 6 further support the notion of alignment that is embedded in the discussion of adapting versus standardizing strategies for serving domestic and foreign markets (e.g., Leavitt 1983; Szymanski, Bharadwaj, and Varadarajan 1993; Walters 1986). We find that it is not necessarily adaptation that holds the key to successful new product performance in foreign markets. Rather, adaptation along selected product facets and selected dimensions of the organization and its strategies is what holds the keys to new product success in an international context. Specifically, we find that adapting international marketing strategy along the following dimensions can be important to achieving success in Asian versus North American markets: technological sophistication of the product, marketing synergies, market orientation, and senior-level support (see Table 6). These data therefore not only document the potential value of product, organizational, and strategic alignment for fostering stronger predictor–performance relationships but also document the specific elements for which fit may be considered an imperative for effective new product performance.

Managers' Perceptions

The meta-analysis also provides initial evidence that attests to the role of divergent managerial perceptions in new product performance. There is a growing stream of research in management that documents the correlation between poor firm performance and inaccurate managerial perceptions (e.g., Starbuck and Mezias 1996; Sutcliffe 1994; Thomas, Clark, and Giola 1993). Inaccuracy has been defined in terms of deviation from a comparison with a more objective standard as well as lack of consensus among parties (Kruglanski 1989). These inaccuracies are thought to occur because of managers' selective attention, perceptual screens, personal biases, collective blindness, tunnel vision, functional fixedness, strategic myopia, and/or contested belief structures (Walsh 1988).

In this regard, the findings from the meta-analysis indicate that management perceptions can differ from objective estimates of performance, and these differences can have a statistically significant effect on the magnitude of the estimated relationships for several predictors of performance (see "Subjective Versus Objective Criteria" column in Table 6). These predictors include products meeting customer needs, dedicated human resources, technological proficiency, reduced cycle time, and cross-functional integration. We further find that a failure to achieve consensus among senior and product managers is manifested in new product performance levels (see "Senior Versus Project Manager" column in Table 6); several of the performance correlations differ to a statistically significant degree depending on whether the data is gathered from managers at the senior or product level. For example, these perceptual disparities account for differences in the estimated relationships for performance with order of entry, structured approach, marketing task proficiency, senior management support, and likelihood of competitive response. Disagreements among managers can lead not only to dysfunctional conflict (Tjosvold 1985) but also to inferior new product performance when the strategies initiated by one party or the other are inappropriate or ill-supported. Thus, although the data reported here cannot address the direct effects of perceptual divergence or disagreements among managers on new product performance, the data document the contingency effects of disparate perceptions on the drivers of new product performance, thus providing new insight for managers and researchers.

LIMITATIONS

As is widely recognized and documented in the meta-analysis literature (Hedges and Olkin 1985; Hunter and Schmidt 1990), any quantitative synthesis is constrained by the nature and scope of the original studies on which it is based, and these limitations should be borne in mind when the findings presented here are interpreted. First, not all of the studies reported correlations, and not all the authors of these could provide us with correlational data. As a result, some studies could not be incorporated into the meta-analysis. Second, the cross-sectional nature of the original studies delimits our ability to make confident causal inferences. Although time-series data would be most desirable for these purposes, they are unavailable in the original studies, and therefore a reliance on cross-sectional data for making causal inferences naturally exists in the product innovation literature. Third, we have previously acknowledged that the relationships reported in the original studies could be positively biased because of oversampling from the efficient frontier of firms. Firms that fail to innovate successfully have likely exited the market and are not captured in the databases used in product innovation studies. Unfortunately, a meta-analysis is not equipped to identify, estimate, or correct for this artifact in the original studies. Fourth, a meta-analysis is constrained to examining moderating elements that can be coded from the extant literature. That the moderating elements that could be coded do not fully account for the variance in the performance correlations indicates that additional measurement factors (e.g., sampling plan: convenience sample versus probability sample; respondent characteristics: years in the organization, new product involvement) and/or contextual factors (e.g., company size, industry, longevity) need to be modeled and reported in future studies on new product performance.

DIRECTIONS FOR FURTHER RESEARCH

In addition to overcoming these sampling, modeling, and information reporting deficiencies, studies should concentrate on modeling elements that have shown initial promise as antecedents to new product success. One element is product quality, which has been widely acclaimed in the popular press as an important and distinct component (i.e., something other than all nonprice attributes) that affects consumer choice. The few correlations ($n = 6$) for product quality with new product performance in our database also document that, on average, product quality has an appreciable effect on how well new products perform (mean $r = .40$, $p \leq .05$). Nonetheless, a paucity of research attention has been directed at specifying product quality separately as an antecedent to new product performance.

Similarly, few attempts have been made to model how firms generate ideas for new products and how successful idea generation and success at each of the other phases of the new product initiative eventually translate into new product success. This void in research attention persists even though the generation of new product ideas is arguably the first step in a cumulative new product development process (Booz-Allen & Hamilton 1982); predevelopment task proficiencies and new product performance are, on average, positively correlated ($r = .46$; see Table 4); and firms that attain high marks in new product introductions generally are shown to be more successful at generating and screening new ideas (e.g., Barczak 1995; Cooper 1984). These deficiencies in the new product performance literature suggest that modeling firm proficiencies at each stage of the new product development process for their effects on new product performance could provide valuable insights to managers and academic researchers.

This study also highlights a need for research directed at capturing the interrelationships among the predictors of new product performance. As our synthesis of the literature makes apparent, the overwhelming majority of models of new product performance are main-effect models (for exceptions, see Atuahene-Gima 1995; Song, Montoya-Weiss, and Schmidt 1997; Song and Parry 1997; Song, Souder, and Dyer 1997). This modeling perspective dominates the empirical landscape despite the competing logic to suggest that selected antecedents to performance may play a more prominent role under selected conditions (e.g., order-of-entry effects may be augmented in companies that are more market oriented). Certain antecedents to performance may also indirectly affect performance by affecting other drivers of new product success (e.g., greater economies of scope realized from the likely association between greater cross-functional integration and greater cross-functional communication). Therefore, the opportunity presents itself to advance understanding by formulating and testing models that capture the interrelationships among the predictor variables. These more sophisticated models represent natural extensions of current research efforts directed at explicating the drivers of new product success. More important, these and other research directions that become apparent as evidence accumulates must be pursued to formulate a knowledge base that can be used by managers to improve new product performance effectively.

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