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The Knowledge Strategy Orientation Scale: Individual Perceptions of Firm-level Phenomena

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One of the most serious threats to the relatively new field of strategic management research is poor construct measurement (Boyd *et al.*, 2005). Due to the relatively complex nature of strategic management variables, quality of measurement is crucial (Godfrey and Hill, 1995) and strategic management research must place greater emphasis on research design, construct validation, and more sophisticated analytical techniques (Bergh, 2001). Many researchers tend to operationalize latent constructs with the use of proxy variables. For example, Boyd *et al.* (2005) found that constructs such as available organizational resources, public profile, core rigidity, and ability to initiate competitive action have all been operationalized by single-item archival measures of organizational size. Additionally, organizational size can be measured as number of employees, number of products, number of production facilities, or any of at least a dozen other measures. The reliance on single-item measures to the exclusion of multi-item scales virtually ensures that research is conducted with unreliable measures that attenuate results. More importantly, there is a clear question of validity. Does organizational size truly represent core rigidity, ability to initiate competitive action, or something altogether different? Additionally, Payne *et al.* (2003) suggest that the use of archival data has several disadvantages. These include the fact that the data may have been originally collected for some other purpose, there may be

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missing data points, archival data may be susceptible to experimenter bias as some researchers might examine the data before they propose hypotheses, and that archival data may not be readily analyzable. Given that all of the above are distinct problems plaguing strategic management research, the truly important issue is that there is no real valid representation of many key constructs.

In fact, Boyd *et al.* (2005) call for the development of new multi-indicator measures for constructs in strategic management research, especially for more contemporary approaches to strategy. Traditional research in strategic management has used a variety of measures for the Miles and Snow (1978) typology of prospectors, analyzers, defenders, and reactors, and the Porter (1980) typology of low cost, differentiation, and focus. However, these approaches to strategic management have been criticized for a variety of reasons (see Grant, 2005). Today, the school of strategy that is attracting a wide degree of attention is the knowledge-based view of the firm, with its typology of exploration and exploitation knowledge strategies. However, an acceptable multi-indicator measure of these constructs has not been generally accepted in the literature.

Thus, the purpose of our study is to examine the factor structure of responses to items designed to measure the knowledge strategy constructs of exploration and exploitation and to provide evidence of external validity using other measures of theoretically-related variables. In keeping with this concern for greater methodological rigor we suggest that the further delineation of these two constructs is appropriate and necessary for future research in this area. In the sections that follow, we give some insight into the theoretical background of our focal constructs, an overview of our analytical methods, the results of our analysis, and a discussion of these results.

THEORETICAL BACKGROUND

A knowledge strategy can be viewed as a firm's set of strategic choices regarding two knowledge domains: 1) exploration, or the creation or acquisition of new knowledge and 2) exploitation, or the ability to leverage existing knowledge to create new organizational products and processes. A firm's knowledge strategy guides its resource allocation—the degree to which the firm focuses its resources on either generating radically new knowledge or incrementally enhancing the existing knowledge base (March, 1991; Bierly and Chakrabarti, 1996). In addressing these trade-offs, March (1991) argued that exploitation is likely to maximize profits in the short run, and that exploration is more likely to maximize long-term firm success. Accordingly, exploration entails higher costs and increased risk for a firm, but is more likely to lead to a sustainable competitive advantage. However, concentrating resources too heavily on exploration may prevent firms from reaping the benefits that come from developing these knowledge breakthroughs. Focusing on exploration tends to slow down the development and refinement of skills and processes associated with the firm's current competencies. On the other hand, a strong commitment to an exploitation strategy entails trade-offs as well. According to March (1991), organizations that focus on the incre-

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mental knowledge gain associated with exploitation may find themselves to be experts in areas that have become obsolete, thus getting better and better at things that customers no longer value.

Exploration and Exploitation Constructs

Conceptualizing exploration and exploitation as two separate constructs implies that they are not simply the two extremes of a single continuum (wherein movement toward one strategy inherently means movement away from the other). Rather, they are two sets of strategic choices, each positioning the firm to develop their intellectual capital in a specific direction, toward excellence in either the creation and acquisition of new knowledge or the leveraging of existing knowledge. In essence, the orthogonal nature of the constructs indicates that firms may pursue one, both (simultaneously), or neither of the strategies. Because certain strategic choices, such as the decision to develop competence in a specific technology, may be necessary to both exploration and exploitation, and therefore would represent overlap in the two sets of strategic choices, we expect a moderate degree of positive correlation between the two constructs. Researchers (March, 1991; Bierly and Chakrabarti, 1996; Zack, 1999) have made claims as to the existence of differentiated knowledge strategies; however, there has been very little empirical research conducted in this area. Using a cluster analysis, Bierly and Chakrabarti (1996) did find evidence of distinct knowledge strategies, but their study was limited to large resource-rich pharmaceutical companies. Yet we believe each orientation to have enough unique elements that exploration can be viewed as independent and distinct from exploitation.

The general argument made by many of the researchers mentioned above is that choosing between exploration and exploitation necessitates trade-offs, and therefore the two strategies are substitutes and, thus, negatively correlated. According to this view, firms that develop competencies in exploitation are likely to focus more of their resources on further exploitation and fewer resources on exploration and vice versa (Levinthal and March, 1993). Basically, this view stresses the value of specialization and efficiency of learning. An alternative perspective, proposed by Knott (2002), is that exploration and exploitation are complements rather than substitutes. Firms that develop the capabilities necessary to foster exploration are also more likely to engage in exploitation, and vice versa. Even though there are difficulties in simultaneously pursuing exploration and exploitation (as described above), there are also organizational systems and human resource practices that support both. More specifically, team-based structures, an organizational culture that values and promotes change, open communication channels, and human resource practices that promote creativity and innovation will help to sustain both exploration and exploitation (Bierly and Daly, 2002). Consistent with this perspective, Helfat and Raubitschek (2000) argue that successful exploitation (referred to as incremental learning) in the past can lead to and support exploration (referred to as step function learning), and that current exploration promotes future exploitation. Anecdotal evidence that

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some companies can successfully pursue exploration and exploitation simultaneously is provided by Knott's (2002) case study of Toyota, Ichijo's (2002) study of General Electric, and Helfat and Raubitschek's (2000) studies of Sony, Canon, and NEC.

Consistent with Knott's (2002) perspective, we conceptualize explorer and exploiter as independent constructs and have developed two four-item scales to measure individual's perceptions of the knowledge strategy constructs known as exploration and exploitation. Even though the concepts of exploration and exploitation are central components of the popular knowledge-based view of the firm, little research has been conducted to examine the legitimacy and relationship of these constructs. An acceptable measurement tool has not yet been developed that has been properly field tested and widely accepted. The vast majority of articles about exploration and exploitation are either conceptual, use computer simulations (e.g., March, 1991; Lee *et al.*, 2003; Garcia *et al.*, 2003), or are based on case studies (e.g. Knott, 2002; Helfat and Raubitschek, 2000; Holmqvist, 2004; McNamara and Baden-Fuller, 1999). A few researchers use patent, or research and development data, or they focus on the number of new products from a firm as proxies for exploration and exploitation (e.g., Bierly and Chakrabarti, 1996; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001). To our knowledge, only He and Wong (2004) have used perceptual measures gathered in a survey to measure these specific constructs.

Radical and Incremental Innovation

Researchers (e.g., Volberda, 1996; Hedlund, 1994) have pointed out that explorers and exploiters often require very different types of organizational cultures, competencies, and structures. Therefore, once a firm creates a competency in either exploration or exploitation, it is usually more efficient for the firm to continue on that particular path (Levinthal and March, 1993). Additionally, researchers in the field of management of technology have discussed the difference between radical and incremental innovations (Damanpour, 1991; Dewar and Dutton, 1986; Ettlie *et al.*, 1984), which can be viewed as outputs of exploration and exploitation, respectively. Thus, a valid measure of an exploration-based knowledge strategy orientation should be associated with distinctive competencies that are required to develop and implement a radical innovation. Specifically, explorers should be firms that aggressively invest in research and development, are creative in improving product technologies, and have established new product development processes that enhance their ability to bring new products to market quickly. On the other hand, a valid measure of an exploitation-based knowledge strategy orientation should be associated with distinctive competencies that are required to develop and implement an incremental innovation. Exploiters should invest more in new process technologies to reduce their cost structure, and excel at practices that facilitate customer satisfaction and promote continuous improvement, such as total quality management (TQM) and benchmarking. With these conceptualizations in mind we suggest:

H1: Distinctive competencies associated with radical innovation will be more strongly related to an explorer orientation than to an exploiter orientation.

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H2: Distinctive competencies associated with incremental innovation will be more strongly related to an exploiter orientation than to an explorer orientation.

METHOD

Participants

Samples were drawn from employees of small to mid-size manufacturers located in the mid-Atlantic region of the United States. The firms represent a broad spectrum of manufacturing, belonging to 18 different Standard Industrial Classification (SIC) groups, including: Food Products (9 firms), Lumber and Wood Products (10), Printing and Publishing (5), Mechanical and Computer Equipment (8), Measuring, Analyzing and Controlling Instruments (5), Furniture and Fixtures (5), Chemical Products (2), Rubber and Plastics (4), Electronic Equipment (6), Primary Metal Industries (5), Transportation Equipment (3), Fabricated Metal Products (9), Stone and Concrete Products (2), Paper Products (2), Textile Mill Products (1), Apparel (3), Petroleum Refining and Related Products (1), and Miscellaneous (18).

Participating firms were identified through cooperation with state Small Business Development Centers which, using membership lists and small business directories, provided company names and contacts. Almost 90% of these companies met the Small Business Association criteria for definition of a small business, having 500 or fewer employees, with the remaining companies classified as mid-size firms (having between 501 and 1,800 employees). Of firms that were identified as subsidiaries of larger parent companies, only those that operated as independent profit centers (strategic business units) within the larger organization were included. Three surveys were sent to 250 companies that initially agreed to participate in the study. Contacts were asked to give surveys to three individuals working in different positions within the company. To ensure confidentiality and encourage participants to be candid in their responses, each respondent enclosed and sealed their survey in an envelope before returning it to the contact person at their company.

As Sharfman (1998) suggests in his study regarding the use of CEOs as sole informants in strategy research, prudent researchers should not rely solely on CEOs, but rather that more informants provide a richer picture of strategy constructs than one informant. Thus, we collected data from a variety of firms using respondents in a variety of positions within those firms. Ninety-eight different companies returned complete and usable surveys from three different respondents in their firms for a response rate of 39.2%. Sample One was comprised of respondents with the following positions in the 98 firms: 9.2% were CEO or President, 18.4% were Human Resources representatives, 33.7% were in Productions or Operations, 6.1% were in Sales or Marketing, 26.5% were in Finance, Accounting, or Administration, and 6.1% were something other. Sample Two was comprised of respondents with the following positions in the firms: 9.2% were CEO or President, 15.3% were Human Resources representatives, 42.9% were in Productions or Operations, 8.2% were in Sales or Marketing, 16.3% were in Finance, Accounting, or Administration, and 8.2% were something other. Sample Three was com-

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prised of respondents with the following positions in the firms: 11.2% were CEO or President, 13.3% were Human Resources representatives, 38.8% were in Productions or Operations, 10.2% were in Sales or Marketing, 19.4% were in Finance, Accounting, or Administration, and 7.1% were something other. Each of these samples is remarkably similar with respect to respondents' positions in the 98 firms and they provide a reasonable cross-section of employees.

Measures

The surveys completed by respondents contained a number of items designed to elicit information about their individual perception of their firm's knowledge strategy orientation and distinctive competencies. Distinctive competencies were selected as potential correlates so that an effort at external validation could be undertaken. Operationalizations of the variables are provided below.

Knowledge Strategy Orientation. Participants completed information on their perception of their employing firm's knowledge strategy orientation via two sub-scales assessing the Explorer Orientation and the Exploiter Orientation. A five-point Likert type scale anchored by 1 = *strongly disagree* and 5 = *strongly agree* formed response scales for both sets of items. The explorer scale items focus on the key elements frequently associated with this construct in the literature: newness, radicalness, and creativity of ideas, technologies and products (March, 1991; Levinthal and March, 1993; Bierly and Chakrabarti, 1996; Zack, 1999). The items are: (1) We frequently experiment with radical new ideas (or ways of doing things), (2) At our company, employees frequently come up with creative ideas that challenge conventional ideas, (3) Compared to our principal competitors, a high percentage of our company sales come from new products launched within the past three years, and (4) We are usually one of the first companies in our industry to use new, breakthrough technologies. Cronbach's alpha for scores on this sub-scale was .71 in Sample One, .74 in Sample Two, and .70 in Sample Three.

The exploiter scale items capture the key elements frequently associated with this construct in the literature: refinement and extension of current technologies and products, increasing efficiency, and improving procedures (Holmqvist, 2004; March, 1991; Levinthal and March, 1993; Bierly and Chakrabarti, 1996; Zack, 1999). The items are: (1) Our company excels at continually improving our existing products, (2) At our company, a strong emphasis is placed on improving efficiency, (3) Our company excels at refining existing technologies, and (4) We frequently adjust our procedures, rules and policies to make things work better. Cronbach's alpha for scores on this sub-scale was .72 in Sample One, .70 in Sample Two, and .75 in Sample Three. Together, the eight items measuring Exploration and Exploitation comprise our Knowledge Strategy Orientation Scale (KSOS).

Distinctive Competencies. As early as 1980 Snow and Hrebiniak used a firm's expertise in various functional areas as a measure of distinctive competencies. In our assessment we focused on the degree of expertise evidenced in the functional areas of the organization and adapted several items from Delaney and Huselid (1996). Participants were asked to as-

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sess their organization's level of expertise in the following eight competency areas. The competencies associated with radical innovation include: basic research and development, product technologies, new product development, and speed in bringing a new product to market. The competencies associated with incremental innovation include: process technologies, knowledge of customer preferences, cost reduction, and benchmarking. For each of these distinctive competencies, participants were asked to indicate, on a scale of 1 to 10, where their firm ranked as compared to their main competitors (with 1 being well below industry average, 5 being the industry average, and 10 being well above the industry average). Although the relationships between our focal constructs and distinctive competencies are analyzed at the item level of distinctive competencies, evidence of the internal consistency of the items associated with radical innovation is provided by Cronbach's alpha of .85 in Sample One, .83 in Sample Two, and .85 in Sample Three. Cronbach's alpha for the items designed to measure incremental innovation was .87 in Sample One, .79 in Sample Two, and .85 in Sample Three. Thus, the distinctive competencies associated with radical and incremental innovation appear to be measuring their intended constructs.

Analysis

Exploratory Factor Analysis. In order to pre-test our items and explore the underlying factor structure of our knowledge strategy orientation subscales, we used principal axis factoring in an Exploratory Factor Analysis (EFA), with a promax rotation, on the data from Sample One. While there is some disagreement on minimum sample size requirements, many methodologists suggest at least five to ten respondents per item are needed for EFA (Comrey, 1988; Hair *et al.*, 1998). We have more than 12 respondents per item. We used the latent root criteria of an eigen value greater than one and a scree plot for the determination of factor extraction. Additionally, we considered items with loadings of greater than .40 to be "substantial" (Floyd and Widaman, 1995) and loadings above .50 to be "very significant" (Hair *et al.*, 1998). Because we have a theoretical basis to support our belief that these constructs are correlated, we used the promax form of oblique rotation. It must be noted that EFA tends to capitalize on the chance characteristics of a sample. Because the purpose of this article is to examine the factor structure of responses to our scale items, we later used confirmatory factor analysis to cross-validate the results of our Sample One EFA.

Confirmatory Factor Analysis. Confirmatory factor analysis allows a confirmatory, rather than an exploratory, approach to determining the underlying structure of observed variables (Harris and Schaubroeck, 1990), and provides a means of assessing the relationships between constructs without the bias commonly introduced by measurement error (Judd *et al.*, 1986). Confirmatory factor analysis is used to determine the extent to which alternative models explain the relationships between items in a scale. Two competing measurement models of strategic orientation were evaluated in this study. The alternative CFA models were: (a) a one-factor model that forced all items designed to measure Explorer and

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Exploiter onto a single factor of Knowledge Strategy Orientation and (b) a two-factor model that forced the Explorer items and the Exploiter items onto separate factors. In each model, error variances for the items were not allowed to correlate. Should the one-factor model provide a fit of the data equivalent to the two-factor model, it would indicate a single underlying latent construct (i.e., Explorer and Exploiter as opposite ends of an unidimensional knowledge strategy continuum). If the two-factor model should provide the better fit than the one-factor model, then our conceptualization of Explorer and Exploiter as distinct and independent constructs will be supported.

As suggested by Thompson and Daniel (1996), CFA is most useful when the researcher tests *a priori* models, because more effective decisions can then be made about the viability of the target model. Because the *a priori* models above are nested, the chi-square difference can be used to test for significant differences between the models. If the chi-square difference is significant, it indicates that the more complex two-factor model fits the data significantly better than the simpler one-factor model.

Hu and Bentler (1998, 1999) recommend that several goodness-of-fit tests be conducted and that their resulting indices be reported. These indices are of two types: absolute and incremental. An absolute index tests how well the model covariance matrix reproduces the sample covariance matrix while an incremental index tests the fit of the hypothesized model as compared to a baseline model. The most commonly-used absolute fit index is the chi-square test that assesses the discrepancy between the implied covariance matrix of the hypothesized model and the sample covariance matrix. A non-significant chi-square is the desired result of this test as it suggests the model may be a reasonable approximation of the data. However, many researchers (c.f. Fan *et al.*, 1999; Hu and Bentler, 1995) have cautioned that using the chi-square test as an assessment of fit can be confounded by sample size because as sample size increases, the chance of the chi-square test supporting a fit of the data decreases. Thus, small differences between the sample covariance matrix and the reproduced covariance matrix may be determined to be statistically significant and lead to rejection of the model. With this in mind, supplemental absolute indices were employed.

Another absolute index, the standardized root mean square residual (SRMR) is reported as a summary statistic based upon residuals between the elements of the implied and observed covariance matrices. The standardized root mean square residual ranges from 0 to 1 and values close to 0 are preferred. In fact, Hu and Bentler (1998, 1999) suggest that researchers always use the SRMR to assess model fit because of its sensitivity to simple model misspecification (misspecified factor correlations). They suggest that target values of the SRMR should be less than .08 in order to indicate adequate model fit. Another absolute fit index, the root mean square error of approximation (RMSEA), is reported in this study as well. The RMSEA assesses lack of fit based upon model misspecification and provides a measure of this discrepancy per degree of freedom (Browne and Cudeck, 1993). This fit index is quite sensitive to complex misspecification (i.e., misspecified factor loadings; Hu and Bentler,

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1998). It ranges from 0 to 1, with target values of less than .08 indicating adequate fit (Browne and Cudeck, 1993).

Incremental fit indices are also recommended (Hoyle and Panter, 1995; Hu and Bentler, 1999) to assess model fit. The comparative fit index (CFI) developed by Bentler (1990) is reported here. It is sensitive to misspecified factor loadings (Hu and Bentler, 1998) and assesses the improvement of fit of the hypothesized model over the null model. The null model is an independence model in which variables are hypothesized to be uncorrelated. The CFI ranges from 0 to 1, and values greater than .95 have recently been advocated (Hu and Bentler, 1999) as an increase from earlier target values greater than .90 (Hoyle and Panter, 1995).

RESULTS

Sample One EFA Results

In Sample One, our principal axis analysis resulted in two factors with eigen values of 3.409 and 1.086 being extracted that explained 56.15% of the variance. As we envisioned, our promax oblique rotation resulted in each Explorer item loading more highly on one factor than the other and each Exploiter item loading more highly on the other factor. Three of four Explorer items showed "very significant" loadings greater than .60. Two of four Exploiter items showed "substantial" loadings greater than .40, while another item showed "very significant" loading. See Table 1 for the resulting pattern matrix. With this factor structure in mind we then cross-validated these results on the data from Samples Two and Three using CFA.

Item Level Statistics for Samples Two and Three

Each CFA measurement model was estimated in this study using LISREL 8.71 software (Jöreskog and Sörbom, 2004). A component of the LISREL software, PRELIS 2.30, was used to assess univariate normality and to generate the covariance matrix upon which the CFA was conducted. Kline (1998) advocates upper boundaries of 3.0 for skewness and 8.0 for kurtosis as indicators of univariate normality.

Sample Two. The univariate data for the Explorer and Exploiter scales were approximately normally distributed with skewness for the eight manifest indicators ranging from -0.88 to 0.39, and kurtosis ranging from -1.56 to 1.45 (see Table 2). Based upon the descriptive statistics for the sample, it appears that the data were approximately normally distributed. Therefore, the maximum likelihood (ML) method of estimation was employed in CFA.

Sample Three. The univariate data for the Explorer and Exploiter scales were approximately normally distributed with skewness for the eight manifest indicators ranging from -1.10 to 0.44, and kurtosis ranging from -1.39 to 1.31 (see Table 2). Based upon the descriptive statistics for the sample, it appears that the data were approximately normally distributed. Therefore, the maximum likelihood (ML) method of estimation was employed in CFA.

Confirmatory Factor Analysis Results

The eight items comprising the Explorer Orientation and Exploiter Orientation scales were subjected to

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Table 1
Pattern Matrix for Principal Axis Factor Analysis in Sample One

	Factor	
	1	2
Explorer 1	**.763**	-.057
Explorer 2	**.674**	.048
Explorer 3	**.626**	.044
Explorer 4	**.356**	.243
Exploiter 1	.159	**.535**
Exploiter 2	.047	**.300**
Exploiter 3	-.135	**.993**
Exploiter 4	.282	**.429**

Note: Largest factor loadings in bold.

CFA. Two models were compared: a one-factor model forcing all eight items onto the same factor and a two-factor model forcing the Explorer items and Exploiter items onto their respective factors. Error terms were not allowed to correlate in either model, and in the two-factor model items were not allowed to cross-load. See Table 3 for the fit indices of these two models in our samples.

Sample Two. The most complex model was the two-factor model, which resulted in CFI = 0.92, RMSEA = 0.097, and SRMR = 0.065. The SRMR indicates good fit of the data to the model, and the RMSEA and SRMR are only slightly outside the recommended thresholds. The more parsimonious one-factor model resulted in CFI = 0.79, RMSEA = 0.16, and SRMR = 0.098. None of these indices meets the criteria for good fit. Additionally, the χ^2 for the two-factor model was 39.60 ($p < .001$), while the χ^2 for the one-factor model was 73.24 ($p < .001$), resulting in a $\Delta\chi^2$ of 33.64 ($p < .001$). The significant $\Delta\chi^2$ indicates that the

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Table 2
Item Level Knowledge Strategy Orientation Scale Descriptive Statistics and Correlations

	1	2	3	4	5	6	7	8
Mean	2.77	3.07	2.57	2.84	3.49	4.00	3.43	3.62
Standard deviation	1.15	1.07	1.05	1.00	0.97	0.81	0.93	0.87
Skewness	0.39	0.06	0.44	0.06	-0.86	-1.10	-0.65	-1.11
Kurtosis	-1.12	-1.39	-0.67	-1.07	-0.40	1.31	-0.71	0.43
Explorer 1		0.51**	0.37**	0.42**	0.33**	0.16	0.30**	0.26**
Explorer 2	0.61**		0.20*	0.19	0.41**	0.19	0.27**	0.31**
Explorer 3	0.32**	0.25*		0.48**	0.47**	0.28**	0.30**	0.27**
Explorer 4	0.40**	0.42**	0.29**		0.33**	0.35**	0.30**	0.13
Exploiter 1	0.23*	0.34**	0.32**	0.21*		0.46**	0.48**	0.48**
Exploiter 2	0.30**	0.38**	0.17	0.07	0.46**		0.48**	0.32**
Exploiter 3	0.29**	0.42**	0.01	0.25*	0.58**	0.36**		0.32**
Exploiter 4	0.31**	0.17	-0.02	0.06	0.29**	0.32**	0.33**	
Mean	2.94	3.05	2.69	2.89	3.70	3.94	3.47	3.66
Standard deviation	1.06	0.94	1.06	1.05	0.80	0.80	0.92	0.90
Skewness	0.39	0.05	0.38	0.22	-0.88	-1.14	-0.59	-0.86
Kurtosis	-1.36	-1.56	-0.79	-0.99	0.36	1.45	-0.52	-0.17

Note: N = 98. Sample Two statistics in upper right side of table; Sample Three statistics in lower left side of table.
*$p < .05$ (two-tailed), **$p < 0.01$ (two-tailed).

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Table 3
Fit Statistics for the Knowledge Strategy Orientation Models

Model	χ^2	df	$\Delta\chi^2$	Δdf	p-value	CFI	RMSEA	SRMR
Sample Two[a]								
2-Factor Model	39.60	19	33.64	1	0.000	0.92	0.097	0.065
1-Factor Model	73.24	20	--	--	0.000	0.79	0.160	0.098
Sample Three[a]								
2-Factor Model	35.43	19	12.85	1	0.000	0.95	0.093	0.066
1-Factor Model	48.28	20	--	--	0.000	0.91	0.120	0.080

[a]N = 98

Note: $\Delta\chi^2$ = change in Chi-square; Δdf = change in degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

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two-factor model fits the data significantly better than the one-factor model, providing evidence of the superior fit of the two-factor model.

Kline (1998) suggests that evidence of convergent validity is provided when items specified to measure a construct all have relatively high path coefficients in CFA analysis. He further states that evidence of discriminant validity is provided when intercorrelations between constructs are not excessively high (i.e., > .85). In Sample Two, the standardized path coefficients for the Explorer scale range from .40 to .80, while the standardized path coefficients for the Exploiter scale range from .39 to .68, thus providing some evidence of convergent validity. Confirmatory factor analysis reveals that the disattenuated correlation between the Explorer factor and the Exploiter factor was .59, thus providing some evidence of discriminant validity between the constructs. In an effort at further validating the factor structure of the data, we submitted data from Sample Three to CFA.

Sample Three. Before we could assess the relationship between our Explorer and Exploiter constructs in Sample Three, we assessed the fit of the two-factor model on data from that sample. The two-factor model resulted in CFI = 0.95, RMSEA = 0.093, and SRMR = 0.066. Of these indices, the CFI and SRMR indicate good fit of the data to the model, but the RMSEA is slightly outside the recommended range. The more parsimonious one-factor model resulted in CFI = 0.91, RMSEA = 0.120, and SRMR = 0.080. Of these, only the SRMR meets the criteria for good fit. Additionally, the χ^2 for the two-factor model was 35.43 ($p < .001$), while the χ^2 for the one-factor model was 48.28 ($p < .01$), resulting in a $\Delta\chi^2$ of 12.85 ($p < .001$). The significant $\Delta\chi^2$ indicates that the two-factor model fits the data significantly better than the one-factor model, providing yet more evidence of the superior fit of the two-factor structure.

The standardized path coefficients for the Explorer scale range from .54 to .73, while the standardized path coefficients for the Exploiter scale range from .51 to .75, thus providing some evidence of convergent validity (see Table 4). Confirmatory factor analysis reveals that the disattenuated correlation between the Explorer factor and the Exploiter factor was .67, thus providing some evidence of discriminant validity. See Table 4 for the completely standardized factor pattern and squared multiple correlations for the two alternative models in both samples.

Relationship to Distinctive Competencies

We used a Z-test described by Meng, Rosenthal, and Rubin (1992) to examine our hypotheses that test for significant differences between correlated correlation coefficients. Each of our distinctive competencies is correlated with each of our focal constructs: Explorer and Exploiter.

In Sample Three, two of the four distinctive competencies associated with radical innovation were statistically stronger in their relationship with Explorer than with Exploiter. The significant correlations were between new product development ($Z = 2.152$, $p < .05$) and speed to market ($Z = 2.344$, $p < .05$) in their relationships with Explorer. Z-scores were 0.454 and -0.499 for research and development and product technology, respectively. Thus, there was partial

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Table 4
Completely Standardized Factor Patterns[a] for Alternative Models of Knowledge Strategy Orientation in Three Samples

	1-Factor Models		2-Factor Models			
	Sample Two	Sample Three	Sample Two		Sample Three	
Item	Knowledge Strategy Factor		Explorer	Exploiter	Explorer	Exploiter
Explorer 1	0.71 (0.45)	0.61 (0.28)	0.80 (0.56)	--	0.76 (0.44)	--
Explorer 2	0.69 (0.54)	0.54 (0.25)	0.75 (0.65)	--	0.57 (0.28)	--
Explorer 3	0.37 (0.12)	0.61 (0.34)	0.40 (0.14)	--	0.66 (0.40)	--
Explorer 4	0.49 (0.22)	0.52 (0.27)	0.55 (0.28)	--	0.61 (0.37)	--
Exploiter 1	0.47 (0.35)	0.75 (0.59)	--	0.61 (0.57)	--	0.78 (0.64)
Exploiter 2	0.43 (0.29)	0.46 (0.33)	--	0.46 (0.34)	--	0.49 (0.36)
Exploiter 3	0.56 (0.36)	0.57 (0.38)	--	0.68 (0.54)	--	0.59 (0.41)
Exploiter 4	0.34 (0.14)	0.46 (0.28)	--	0.39 (0.19)	--	0.48 (0.31)

[a]R^2 values in parentheses.

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support for hypothesis one in sample three. Additionally, each of the distinctive competencies associated with incremental innovation were statistically stronger in their relationship with Exploiter than with Explorer. The correlations were between process technology ($Z = -2.021, p < .05$), customer preferences ($Z = -2.468, p < .05$), operating efficiency ($Z = -3.048, p < .05$), and benchmarking ($Z = -2.148, p < .05$) in their relationships with Exploiter. Thus, there was support for hypothesis two in Sample Three. See Table 5 for the correlations and accompanying Z tests.

DISCUSSION

This study examines the individual perceptions of employees regarding the knowledge strategy orientation of their firms. More specifically, we are interested in whether these individuals perceive their organization to have an Explorer or an Exploiter knowledge strategy orientation.

Measurement Implications

We analyzed the self-report data in three samples of respondents using EFA and CFA to examine the factor structure of item responses, the convergent and discriminant validity of the explorer and exploiter constructs, and the relationship of these measures with the measures of distinctive competencies. Our results indicate that our scales are indeed separate factors, as a one-factor model did not fit the data well, but the two-factor model did. The Explorer and Exploiter scales also resulted in scores with acceptable reliability. The factor pattern coefficients were high enough to provide some evidence of convergent validity, while the correlation between the two factors was low enough to provide some evidence of discriminant validity between the constructs. Additionally, we found that each construct was differentially related to the various Distinctive Competencies. Therefore, the results of our analysis provide strong evidence of validity for our Knowledge Strategy Orientation Scale (KSOS).

By forcing our Explorer and Exploiter scale items onto different factors our two-factor model resulted in better indices of fit as evidenced by the superior indices and the Chi-square difference test over the one-factor model. Our results may be enlightening to researchers who use employees' perceptions for analysis of firm-level phenomena. Previous researchers have advocated a self-typing measure of firm strategy (cf. Hambrick, 1989; Snow and Hambrick, 1980). These researchers suggest that as an alternative to researcher inferences about firm strategy from archival data, an organization's managers might acceptably and reliably characterize their firm's strategy. Our analysis suggests that perceptions of firm strategy, as measured by our scale, are consistent regardless of the respondents' position held in a firm.

Our scales both resulted in acceptably high alpha reliabilities (Nunnally, 1978). This level of average inter-item correlation suggests that the Explorer items provide an aggregate measure of one construct and the Exploiter items measure another separate and distinct construct. Additionally, our standardized factor pattern coefficients ranged in Sample Two from .40 to .80 and in Sample Three from .57 to .76 for the Explorer scale. These values ranged in Sample Two from .39 to .68 and in Sample Three from .48 to .78 for the Exploiter scale,

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Table 5
Correlations and Z-tests for Relationship between Focal Constructs and Distinctive Competencies

Distinctive Competencies	Sample Three Correlations		
	Explorer	Exploiter	*Z* score
Radical Innovation			
Research and development	.42**	.38**	0.454
Product technology	.40**	.44**	-0.499
New product development	.56**	.38**	2.152*
Speed to market	.60**	.41**	2.344*
Incremental Innovation			
Process technology	.29**	.47**	-2.021*
Customer preferences	.02	.26*	-2.468*
Cost reduction	.26*	.42**	-3.048*
Bench-marking	.00	.21*	-2.147*

*p < .05, **p < .01.

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thus providing some additional evidence of the convergent validity of our scales. Regarding discriminant validity, our attenuated correlation between the two factors ranged from .40 to .55, but our CFA results show a disattenuated correlation ranging from .59 to .67. Although this indicates that they are indeed correlated, they are different enough so as to not be considered collinear (Kline, 1998), indicating some evidence of discriminant validity. The moderate level of correlation between our constructs as well as the acceptably high alpha coefficients indicate that our respondents conceive of the Explorer and Exploiter knowledge strategy orientations as independent constructs.

Data provided by the measure of our two constructs provided evidence of differential relationships with the distinctive competencies. Almost all of our distinctive competencies were significantly stronger in their relationship with our focal constructs. Specifically, two of four distinctive competencies associated with radical innovation were more strongly related to the Explorer knowledge strategy orientation than to the Exploiter knowledge strategy orientation. The stronger correlations between Explorer knowledge strategy orientation and distinctive competencies associated with radical innovation are consistent with the work of He and Wong (2004). This is a favorable source of external validation as we expect firms that engage in radical innovation to utilize an explorer's knowledge strategy orientation. We also found that each of the distinctive competencies associated with incremental innovation were more strongly related to the Exploiter knowledge strategy orientation than to the Explorer knowledge strategy orientation. These findings are consistent with the theoretical frameworks provided by Bierly and Daly (2002), March (1991), and Levinthal and March (1993).

Managerial Implications

One objective of our development of the KSOS was to address some of the methodological problems of past research in this area: an over-reliance on archival data, the use of single-item measures, and the use of proxy measures for focal constructs. Our study focused on a psychometric evaluation of survey items based upon theoretical insights provided by Holmqvist (2004), March (1991), Levinthal and March (1993), Bierly and Chakrabarti (1996), and Zack (1999) regarding firms' knowledge strategies. Our second objective in development of this new scale was to provide an instrument that would prove useful to managers in the areas of organizational assessment and strategic planning.

When compared to measurement based on single-item measures, archival data, and proxies, a scale such as ours captures the essence of the Explorer and Exploiter constructs much more accurately. The relatively simple and easy to use scale allows managers to gather primary data about their organizations regarding knowledge strategy orientation, and then use the subsequent analysis to inform decisions that pertain to knowledge management and innovation in their firms. We believe the establishment of a commonly accepted measure of knowledge strategy orientation will help managers to identify organizational strengths and weaknesses within the focus areas delineated by each of the KSOS items (e.g., radical

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versus incremental innovation). Managers need to be able to objectively evaluate their organization's knowledge base, discern how knowledge is transferred and integrated in the organization, and develop knowledge strategies that maximize the potential of their knowledge base.

Use of the KSOS will help managers to better understand and assess their strategic choices regarding the creation or acquisition of new knowledge and the ability to leverage existing knowledge. The firm's knowledge strategy orientation should help to guide managerial choices regarding resource allocation in the firm. For example, an exploration orientation may support the allocation of additional resources to new product development within a small firm that relies on advances in technology to ensure its competitive viability. In low-tech firms resources may best be used to support incremental continuous improvement and a focus on marketing (e.g., reinforcing brand image) rather than on attempts at radical innovation. These choices are particularly important to smaller firms that are more resource constrained and thus cannot pursue both the Explorer and Exploiter strategies simultaneously.

Geiger and Cashen (2002) address the important issue of resource allocation and its affects on innovation in their article exploring the effects of organizational slack. The KSOS, which helps firms identify their propensity for radical versus incremental innovation, could be very useful in future research of these issues. Additionally, the scale could be used by researchers exploring ways to retain and manage intellectual capital in organizations. For instance, Droege and Hoobler's work (2003) discusses the relationship between employee turnover and tacit knowledge loss in organizations. Their research indicates that allocating resources to enhance and promote social network structures within the organization is vital to retaining tacit organizational knowledge. Studies such as these indicate the potentially widespread usefulness of the KSOS measure in further research and practical application in the management field.

Limitations and Suggestions for Future Research

Scale construction is a dynamic process, with the objective of continually improving the measurement of a construct (DiTommaso *et al.*, 2004), and therefore we suggest that the validity characteristics of our scales need further study. Accordingly, the generalizability of our findings is limited by the nature of our samples: three (although very heterogeneous with respect to position held) groups of respondents from small manufacturing companies located in the mid-Atlantic region of the U.S. However, we do acknowledge that a conceptual difference exists between "position" and "level" in an organization such that some positions exist at different levels and some levels do not align perfectly across functions. For example, in an accounting department one might find three levels: accounting directors, cost accountants, and accounts payable clerks. In a manufacturing department one might find first-line supervisors, journeyman welders, and welder helpers. In the organizational hierarchy, accounting directors and first-line manufacturing supervisors might be on different levels with only a few levels of management above the former, but numer-

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ous levels above the latter. Clearly, a difference exists between positions, functions, and levels and future research might seek to explore differences in perceptions of a firm's knowledge strategy orientation both between and among positions, functions, and levels in a particular firm. Another step might be to employ our scales in a predictive validity study using large organizations in both manufacturing and service industries. This would allow for the assessment of the measurement characteristics of our scales in different samples and in different domains of industry. We believe that our KSOS can provide researchers with an alternative measure of firms' strategic orientation and that employees' perceptions of firm strategy can help overcome some of the measurement shortcomings of using archival data as proxies for organizational-level variables.

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increase profits at the expense of suppliers and employees, but not customers. The findings also suggested that customers were given the highest priority while employees were viewed as the lowest priority of business.

Human Resource Safety Practices and Employee Injuries.................... 397
Kristy J'Lyn Lauver

This study investigates how organizations can improve employee safety by examining the association Human Resource (HR) safety practices (selection, training, evaluations, compensation) have with employee injuries. Top and operational-level managers at forty-eight organizations completed a survey regarding their safety-related HR practices and provided organizational injury records for the past five years. The findings of this study contribute to the study of safety, by identifying HR safety practices (individual compensation, group compensation, previous work experience, and drug-testing) that have a positive association with reduced organizational-level injuries.

The Knowledge Strategy Orientation Scale: Individual Perceptions of Firm-level Phenomena.. 414
Brian K. Miller, Paul E. Bierly III and Paula S. Daly

We developed the Knowledge Strategy Orientation Scale (KSOS) to overcome some of the methodological problems inherent in strategic management research: an over-reliance on archival data, the use of single-item measures, and the wildly varying use of proxy measures for focal constructs. This article presents a psychometric evaluation of survey items based upon theoretical insights provided by Holmqvist (2004), March (1991), Levinthal and March (1993), Bierly and Chakrabarti (1996), and Zack (1999) regarding firms' knowledge strategies. In a pre-test, principal axis factor analysis on one sample of respondents from 98 different firms indicates that two factors explain a majority of the variance in the eight items and that each item intended to measure Exploration and Exploitation loaded on the appropriate factor. This factor structure is cross-validated on a second sample from the 98 firms using confirmatory factor analysis. The factor structure is reconfirmed in a third sample of respondents from the 98 firms. Regarding the strength of the relationship

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between exploration, exploitation, distinctive competencies associated with radical innovation, and distinctive competencies associated with incremental innovation, we find full support for one of our hypotheses and partial support for the other. Our results suggest that persons holding different positions in a firm (from CEO to Production Worker) are likely to validly respond to our scale items, that respondents reliably envision the two constructs that we measure as separate entities, and that these separate entities related mostly as hypothesized to various distinctive competencies.

Enhancing Product Recovery Value in Closed-loop Supply Chains with RFID 436
John K. Visich, Suhong Li and Basheer M. Khumawala

Closed-loop supply chains' integration of the forward and reverse supply chains is an emerging area of interest as firms seek to reduce costs of returns, increase profits through value recovery and meet more stringent environmental standards. Closed-loop supply chains have a higher level of complexity than stand alone forward supply chains or reverse logistics networks due to the uncertainty in the timing, location, quantity and quality of returned goods. This uncertainty inhibits effective and efficient product recovery operations and hence has an adverse impact on the value of recovered products. A key to reducing the uncertainty in closed-loop supply chains is accurate and timely information. Radio Frequency Identification (RFID) technology has the potential to provide such information. The purpose of this article is to introduce how RFID is and can be utilized by the various participants in a closed-loop supply chain. We also describe how RFID can be used to enable decision making during the return process and to enhance the various value recovery options in a closed-loop supply chain. In addition, we provide direction for the implementation of RFID systems in closed-loop supply chains.

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