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Developing and Validating Field Measurement Scales for Absorptive Capacity and Experienced Community of Practice

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Research on knowledge transfer in organizations has been hampered by the lack of tools yielding valid scores for studying critical constructs in concert. The authors developed survey measures of absorptive capacity (the ability to transform new knowledge into usable knowledge) and experienced community of practice (the extent to which a person is engaged with the given practice community) to provide tools appropriate for field research. A holdout sample of 1,971 engineers in a Fortune 100 science/technology company yielded 583 responses. Confirmatory factor analysis was used to assess internal structure, and convergent and discriminant evidence of validity. Path analysis was used to assess criterion-related validity. Results demonstrate that the new measures are internally consistent, are related in meaningful ways to other organizational variables, and provide distinct explanatory power. An additional 231 responses from a second Fortune 100 science/technology company provides cross-validation.

Keywords: absorptive capacity, community of practice, knowledge management, organizational learning

Fostering and managing knowledge within an organization is critical to sustain competitive advantage (Winter, 1987; Winter & Szulanski, 2001). Griffith, Sawyer, and Neale (2003) presented a framework of the dynamics of knowledge development and transfer in modern organizational settings, including virtual work. They argued that individual and social knowledge (Spender, 1996) combine to have organizational impact, but this transition is moderated by three factors: two at the

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team level of analysis—absorptive capacity (ACap; Cohen & Levinthal, 1990; Szulanski, 1996) and transactive memory (Moreland, Argote, & Krishnan, 1998; Wegner, 1986)—and one at the level of organizational or professional community—community of practice (CoP; Brown & Duguid, 1991; Leonard & Sensiper, 1998).

Absorptive capacity describes the ability of an organizational unit to use past experiences to increase the ability to learn and apply new knowledge (e.g., Cohen & Levinthal, 1990). Transactive memory is memory about the knowledge and expertise of another person (e.g., Lewis, 2003). A community of practice is a set of people bound together through common interest and language with the goals of open communication and exchange and retention of pertinent information (e.g., Wenger, 1998b). Experienced community of practice (eCoP) is the subjective experience of membership in a community of practice.

While each of these constructs has received significant individual attention in the literature, Griffith et al. (2003) argued that these constructs are more powerfully, and appropriately, considered in conjunction with one another. We describe these three constructs as part of the organization’s knowledge transfer ecosystem. The metaphor of an ecosystem reflects how multiple components within the system work in symbiotic ways to transition individuals’ knowledge into organizational outcomes. The knowledge transfer ecosystem depends on the interaction and participation of individuals, teams, organizations, and the community/society. Griffith et al.’s (2003) work is theoretical. Empirical work has been limited by the lack of scales yielding valid scores for measuring ACap and eCoP appropriate for field research (transactive memory has been effectively addressed by Lewis’s (2003), scales). We began with the few extant measures. Our goal was distinct, field-appropriate measures of ACap and eCoP, following the Standards for Educational and Psychological Testing (American Educational Research Association, American Psychological Association, & National Council on Measurement in Education, 1999) to define the constructs, and develop and evaluate our measures.

Definition and Proposed Model of ACap

ACap is the ability to transform new knowledge into usable knowledge through the processes of assessment (identification and filtering of valuable information), assimilation (conversion of new knowledge into usable knowledge), and application (using the knowledge). We have termed the coordinated processes the three “As” approach to ACap. In our definition, we reintegrated a component of value identification that was originally proposed by Cohen and Levinthal (1990) and most recently recommended by Todorova and Durisin (2007). We used this definition of ACap because it encompasses the manifestation of the different processes that an individual as well as an organization would go through to transform new knowledge into usable knowledge for application. We have stayed with a three-pronged definition following Cohen and Levinthal (1990), but with the understanding of the dynamic,
staged, model suggested by Zahra and George (2002). The three coordinated processes tap the conceptual essence of A Cap, implying that we can make inferences about A Cap in the presence of assessment, assimilation, and application. Figure 1 provides a visual representation of the A Cap model.

Assessment. In the context of A Cap, assessment is the ability to identify and filter knowledge that will be valuable (i.e., can be used or exploited at some future time). Previous experiences influence our ability to identify and filter useful knowledge. Broadbent (1958) proposed a filter theory arguing that there is a bottleneck prior to recognition that regulates what information gets to the pattern recognition stage. This filter system reduces the otherwise overwhelming amount of information to which we are exposed.
**Assimilation.** Assimilation is the process of cognitively organizing acquired knowledge to make it accessible for future use. Assimilation includes the acquisition of the knowledge as well as processing knowledge in preparation for future use. For example, a corporate tax accounting seminar exposes a certified public accountant (CPA) to information about the intricacies of tax law. The CPA needs to process and store (assimilate) new tax knowledge for proper future application as it pertains to client taxes. Zahra and George’s (2002) perspective would code the outcomes of assessment and assimilation as potential absorptive capacity.

**Application.** The application process describes the ability to take the assimilated knowledge, recognize a situation where the knowledge can be exploited, and use it. Application aligns with Zahra and George’s (2002) realized absorptive capacity. The application of the new knowledge may or may not be for the anticipated use. People can creatively exploit the new knowledge in a completely unique way. The CPA described above applies the intricate tax knowledge acquired at the seminar to develop a creative financial algorithm to predict recessions in the economy. This represents one person’s application of the seminar material in relationship to another field.

**Prior Measurement Scales for Absorptive Capacity**

Our extensive review found a limited focus on quantitative measures for ACap at the individual or team units of analysis. There are a variety of quantitative organizational-level studies. Metrics include R&D budgets, number of PhDs employed, and so on. Please see Zahra and George (2002) for a review. This was consistent with prior reviews. Lane, Koka, and Pathak (2006) provide a thematic analysis of 289 articles and noted a lack of measurement instruments for ACap. Zahra and George (2002) found that even though there have been many studies focusing on ACap, only Szulanski (1996) contained a measurement scale. (See also Szulanski, Cappetta, and Jensen (2004) who used the same scale.) Jansen, Van Den Bosch, and Volberda (2005) also concluded that scales delimiting potential and realized ACap are necessary for field research. In the sections below we provide an overview of the extant measures in preparation for presenting our approach that keeps distinct ACap, eCoP, and transactive memory.

Szulanski (1996) focused on studying *stickiness* of knowledge transfer and developed a nine-item scale intended to capture an individual’s ability to value, assimilate, and apply knowledge. Szulanski’s scale provides a valuable guideline to developing a survey scale for ACap. However, we feel Szulanski’s (1996) scale has insufficient focus on prior knowledge as a mechanism for assessing knowledge. Szulanski placed emphasis on skills and competencies as an implicit way of alluding to prior experiences that determine the ability to absorb knowledge. We argue that a person’s knowledge absorption capacity may or may not be influenced by competency within a specific role; with the determinant being an individual’s opportunity to exploit their
prior experiences in regard to the best practice or knowledge being transferred. In addition, his scales lack statements pertaining to the filtering process of the assessment phase of ACap where valuing the information or its source are important abilities. Also, some of Szulanski’s items have conceptual overlap with components of transactive memory and eCoP, and finally, Szulanski’s study was focused on the firm/organizational level transfer of a best practice rather than an individual’s absorptive capacity to exploit new knowledge. Still, Szulanski’s scale provides a key reference point for the creation of our items. We also found value in Jansen et al.’s (2005) work, though it was not available during our scale development and initial data collection. They also used the idea advocated by Zahra and George (2002) in regard to the existence of potential and realized ACap. However, Jansen et al.’s model is represented by four distinct dimensions and we present three. Transformation is an additional dimension contained within their model and is identified with realized ACap. While they found discriminant validity among their subscales, we raise the same concern as with the Szulanski (1996) measures: Though the items factor appropriately for their particular applications, they focused on ACap in a more standalone context than we do. Our goal was to be able to address ACap, eCoP, and transactive memory as independent constructs in an integrative model of organizational knowledge processes. Additionally, the Jansen et al. (2005) measures are less valuable for our goals given that they are relatively context specific (e.g., corporate settings and/or a separate headquarters).

**Definition and Proposed Model of eCoP**

A community of practice is a set of people bound together through common interest and language with the goals of open communication and exchange and retention of pertinent knowledge (e.g., Wenger, 1998b). We proposed that there are four components of experienced CoP: open communication, shared vocabulary, remembering previous lessons, and learning from each other. Past CoP theory and research has individually identified these four components as manifestations of CoP, but not within a comprehensive model of CoP. We emphasize experienced CoP to highlight the difference between organizational practices (e.g., being assigned to a community of practice) and the reality of there being a community of practice. Below we describe each component and justify its importance and identification of eCoP. Figure 2 provides a visual representation of our model of eCoP.

**Open communication.** Without open communication, interaction would not occur between community members and, therefore, the community would dissolve. Establishment of trust and motivation to share information is requisite for the establishment of a successful community of practice. Open communication is also synonymous with free communication, which members can establish through face-to-face interactions as well as virtual methods of interaction, including email,
message boards, group email aliases, and so on. We intended this subcomponent to measure whether or not there is trust within the community to share information and the ease of interactions within the CoP.
Shared vocabulary. Within a community of practice, team members create a common lingo to interact with each other to facilitate the transfer of information. In addition, having a shared vocabulary may also be a way for the group to establish a sense of exclusivity. Having this exclusivity adds to the value and motivation for an expert to attend and interact within a community of practice. Even though the expertise will vary within a CoP, as long as a member has a grasp on the common jargon of the community, interaction and learning can take place. This shared vocabulary component also aligns with the aspect of a specific practice or what Wenger, McDermott, and Snyder (2002) described in their structural model of a CoP as a domain. A domain is the sense of a common identity that a CoP must establish to be effective.

Remembering previous lessons. An additional common component of a CoP and the general reason organizations or members create them is to establish an arena where best practices and lessons can be passed on to peers who will benefit from the new information. For example, electronic chip design engineers may discover that there is a more efficient way to lay out components on a printed circuit board. The community of practice provides the best forum to propagate the best practice design process to other engineers and archive it within a community repository.

Learning from each other. Another of the underlying reasons for forming a community of practice is to learn from interactions with people who share the same interest. The focus of group interactions is to share and listen to other community members. If the exchange of information between community members is not valuable and no learning is occurring then either the CoP will become more of a social club or the CoP will eventually fade away (Wenger, 1998a). A CoP not only provides a place where members can learn from previous experiences, but the new information may also catalyze new ways of applying the information within the common practice. To the extent that people feel there is open communication, shared vocabulary, strategies for remembering, and learning from one another—there is greater eCoP.

Method

Although eCoP and ACap can be viewed as a team-level or organizational-level phenomena, both exist as a function of each of their respective individual concepts applied to the members making up the team or organization. This implies that these constructs may be appropriately measured at the individual level. A major concern is whether these measures reflect team-level constructs and can thus be expressed as an aggregation of individual members’ responses to the scale. In other words, is a sum
or average of member responses a meaningful team-level indicator of an eCoP or ACap construct?

If items focusing on members’ responses about the team remain meaningful when aggregated, then there is a conceptual justification for the aggregation. Using ACap as an example, the sum of members’ responses to the item, “People in my team are able to decipher the knowledge that will be most valuable to us” represents the extent to which members believe that the team effectively assesses the value of information that can be eventually assimilated and applied in the future. A low aggregate score reflects limitations regarding the extent to which the team is able to effectively assess the value of new knowledge. A high aggregate score reflects a team that is able to make this assessment. Because of the fact that both high and low aggregate scores are consistent with the definition of the assessment dimension of ACap, aggregating this item is conceptually justified. Likewise, if the scores on eCoP among members of a community of practice are consistent, then those members similarly perceive the existence of a shared communication, vocabulary, and so on, within that community of practice and aggregated scores would reflect a shared experience of that community. Our assessment was that aggregation is warranted across both ACap and eCoP.

Scale Creation

The conceptual and theoretical descriptions of ACap and eCoP suggest they are multidimensional. Both ACap and eCoP manifest in each of their identified latent variables, respectively. To create strong theoretical consistency with our theoretical framework, we employed the survey creation methodology outlined by Sudman and Bradburn (1982). Each researcher independently created a pool of three to five items aligning with our definitions and strong theoretical framework. We then solicited reviews from colleagues and peers to gather feedback about how the items spanned the theoretical space. Theoretical consistency and wording were the main criteria for assessing an item during the multiple rounds of refinement. We sought further content evidence of validity for a field context by showing the questions to (nonparticipating) current employees of our initial field site (TechCo, a Fortune 100 science/technology company). During this session we asked them to comment on the appropriateness of the items for their work setting.

We used a 7-point Likert-type scale for each of the items. Because we designed all items to describe the work setting, an agreement scale was appropriate. The scale ratings were anchored from 1 = strongly disagree to 7 = strongly agree. Both the ACap and eCoP scales are latent constructs not measured directly but rather by their manifestations. The statistical interpretation of a latent ACap and eCoP variable implies that (a) when an ACap exists, it causes assessing, assimilating and applying new knowledge; (b) when an eCoP exists, it causes open communication, shared vocabulary development, remembering, and learning within a particular network of people; and (c) the latent variables of each respective construct covary because they have a common cause.
We created three items each in the ACap scale that indirectly measure the latent variables of assessing, assimilating, and applying new knowledge within the respondents’ team. A high ACap score indicates higher levels of absorptive capacity in regard to the three identified latent variables. We also created three items each in the eCoP scale that indirectly measure the identified latent variables of open communication, shared vocabulary development, remembering, and learning within a particular network of people with whom the respondent shares technical knowledge. A high eCoP score indicates higher levels of experienced community of practice in regard to the four identified latent variables. Designed to be self-report, these items tap the level of existence of ACap and eCoP in the respondent’s experience.

We then administered our survey to a sample of 185 MBA students at two different universities. The MBA students were predominately part-time students holding full-time jobs. All students had at least 3 years of work experience. We instructed the students to respond to the questions with reference to their current or most recent work setting. We took note of any questions or comments the students made during the survey administration, and interviewed several students after completing the survey. This led to further refinement of the wording for clarification of several of the items. We conducted a principal components analysis of the resulting data. That analysis pointed to problems with some of the items that had been reverse scored. Combining the comments of the students with the component analysis results we determined that the reverse worded items merely served to confuse the students and led to poorly fitting factor structures. These results are consistent with substantial research indicating that reverse worded items lead to wording artifacts in factor analyses and reduce reliability of scores using these scales (Schriesheim & Eisenbach, 1995). As a result we rewrote the negative items to have direct worded stems (Bar- nette, 2000) with bidirectional (strongly disagree–strongly agree) response options. We removed some other items that were inconsistent with the intended factor structure and retained the items with the highest item total correlations to reduce the number of items per subscale to make the survey more feasible to administer in a corporate setting (Stanton, Sinar, Balzar, & Smith, 2002). This resulted in the three items for each of the three ACap subscales and for each of the four eCoP dimensions listed in the appendix.

Field Validation Study

Respondents. We sent 1,971 technical account representatives (TARs) within TechCo Web-based surveys as part of a larger study of 3,186 TechCo TARs. TARs are a group of highly specialized technology experts that serve as technical consultants to the TechCo account managers who sell technical solutions to customers. All were full-time employees at TechCo. The population includes 47 different countries. Although data on gender is not available, our observations suggest that this popula-
tion is predominantly male. From this subset of 1,971 TARs, 583 responded for an overall response rate of 29.6%. The number of respondents for each analysis varied because of removal of participants that had no responses on the entire scale, otherwise maximum likelihood estimation was used to model the missing data. Actual Ns for each analysis are reported along with the analyses. The mean number of days employed at TechCo was 1720.89 (SD = 669.50).

Procedure. With the agreement and support of the executive global leadership team of the TARs, we used TechCo’s corporate online survey tool to present the survey (in English, TechCo’s official language). The survey included our refined measures of ACap and eCoP, plus other organizational measures to aid in establishing criterion evidence of validity for our scales as described below. The relevant executive vice president sent a personalized email requesting participation, providing the survey URL and asking for completion within 28 days. This email noted that all teams with a response rate of 80% or higher would enter a raffle to win highly valued TechCo prizes. The email also explained the voluntary nature of the survey and how TechCo would use the data. We sent reminders after 14 and 28 days. We treated all participants in accordance with approved human subjects guidelines.

Other organizational measures. We created additional measures and gathered data from the organization’s archives in preparation for establishing criterion-based evidence of validity. We created two single item measures of satisfaction with the knowledge environment of the firm. The first was “Overall, how satisfied are you with your ability to share your knowledge using the tools and practices available to you at TechCo?” (SatShare). The second was “Overall, how satisfied are you with your ability to find knowledge you need using the tools and practices available to you at TechCo?” (SatFind). We tolerated single items given our and TechCo management’s concern with the length of the survey.

From the organization, we obtained three additional measures. CoPAttend is the number of CoP meetings attended in the past 2 years. These are technical skill-focused communities of practice and TARs become members through passing base-level entrance exams. The TARs can belong to multiple CoPs. TrnWeeks is the total number of all hours of training the participant took in the past 2 years divided by 40 hours. This training is both technical and managerial, eLearning and face-to-face. TechComp is a self-evaluation of technical competency assessed as a self-report; with verification by the TAR’s manager (competency assessments are part of the TechCo human resource practices, which are separate from this study).

Cross-validation sample. Following the initial validation study, we gathered survey responses from a sample of scientists and engineers working in product development teams in a second Fortune 100 science/technology firm (R&DCo). We distributed a Web-based survey to 416 scientists and engineers working in 45 different product development teams. Complete surveys were returned by 231 members.
for a response rate of 56%. The sample was representative of the population with 66% male, 65% White, and the modal age was 36 to 40 years. The sample was highly educated with 45% holding a doctoral degree, 14% master’s degree, and 22% bachelor’s degree.

Results

We used confirmatory factor analysis to assess internal structure, convergent, and discriminant evidence of validity (American Educational Research Association et al., 1999). First, we estimated measurement models with second-order factors for ACap (three first-order factors: assessment, assimilation, and application), and eCoP (four first-order factors: communication, vocabulary, remember, and learning), Figures 1 and 2 present the hypothesized factor models and their standardized item loadings. Hu and Bentler (1999) suggest using multiple fit indices as an effective method (limiting both Type I and II error rates) for evaluating the fit of a specified model to the data. Therefore, we evaluated fit using root mean squared error of approximation (RMSEA), standardized root mean square residual (SRMR), and comparative fit index (CFI; Bentler, 1990). Furthermore, we assessed fit using the cut-off criteria recommendations of Hu and Bentler (1999). They suggested that relatively good fit would be indicated by a value close to .06 for RMSEA, a value close to .08 for SRMR, and a value close to .95 for CFI. Both the eCoP and ACap measurement models represent a relatively good fit of the observed data to their respective measurement models.

We then estimated nested single-factor models for each to evaluate the hypothesized structure of the first-order factors. Table 1 includes the fit statistics and differences in chi-square between the hypothesized factor structures and the nested single-factor models. In both cases, the hypothesized factor structures represent more statistically significant improvement in fit than a single-factor model. This provided strong structural evidence of validity—the models’ hypothesized factor structures are a better fit than the nondifferentiated factor structures.

We next turned to estimating reliability of the scores for this sample (see Table 2). Construct reliability of the scores was evaluated through interpreting the squared standardized factor loadings as estimates of individual item reliability. Furthermore, internal consistency was estimated with coefficient alpha, 95% confidence interval of alpha calculated using two-way random effects in SPSS (SPSS, 2008), and construct reliabilities estimated using coefficient $H$ (Hancock & Mueller, 2001). Coefficient $H$ is “the squared correlation between the latent construct and the optimum linear composite formed from the measured indicators” (Hancock & Mueller, 2001, p. 203). We evaluated estimated construct reliability against a .80 guideline, which has been discussed as an acceptable benchmark for research purposes (Henson, 2001; Nunnally & Bernstein, 1994). All of the subscales met this guideline for
reliability except for the ACap assessment and eCoP communicate scales which both had estimated alpha reliabilities below the .80 criteria. However, only the 95% confidence interval of the ACap assessment scale did not include .80. Furthermore, results from the interpretation of the coefficient $H$ values were the same as the alpha reliability analysis. Thus, in general we feel confident that the shared variance between the constructs and their measures is greater than the shared variance between the constructs and the error variance (Carmines & Zeller, 1979).

**Criterion-Related Evidence of Validity**

As noted above, we had a variety of criterion measures to consider from both company archival data and additional scale items. We conducted a path analysis with latent variable constructs for ACap and eCoP. Because absorptive capacity represents this baseline knowledge necessary to make sense of and use new knowledge, we expected the amount of time spent in training (TrnWeeks) and rated technical competency (TechComp) to lead to heightened ACap. People share and receive knowledge within experienced communities of practice. Thus, we expected attendance at CoP events to relate positively to experienced community of practice. Because communities of practice are the medium for knowledge sharing, we expected satisfaction with opportunities to share knowledge (SatShare) and satisfaction with finding knowledge (SatFind) to be positively associated with experienced community of practice.

We used the full information model for the ACap and eCoP constructs, modeling the first- and second-order factors. Because the exogenous variables are single indicator variables, we modeled the latent variables by fixing the lambda $\times$ coefficients to 1 and setting the error variances to the item variance—$(1 - \text{reliability})$ in which we assumed a reliability of .90 for each measure (Williams & Hazer, 1986). We ran the analysis with those paths expected to be positive free and all other paths from the criterion variables fixed to zero. This initial model did not achieve an acceptable fit of the data to the model (CFI = .87). We then conducted an exploratory analysis to understand the relationships of our measurement model to the exogenous variables.

| Table 1: Confirmatory Factor Analysis: Fit Indices |
|-----------------------------|----------------|-----------------|-----------------|-------------|-------------|-------------|
| Model                        | $\chi^2$  | $df$ | RMSEA | SRMR | CFI | $\Delta \chi^2$ | $\Delta df$ |
| Absorptive capacity (ACap)   |             |      |       |      |     |             |           |
| Hypothesized 3-factor model  | 87.46       | 24   | .08   | .07  | .94 | 176.47**    | 3           |
| Single-factor model          | 263.93      | 27   | .13   | .08  | .78 |             |             |
| Experienced community of practice (eCoP) |       |      |       |      |     |             |           |
| Hypothesized 4-factor model  | 204.37      | 50   | .08   | .05  | .93 | 460.02**    | 4           |
| Single-factor model          | 664.39      | 54   | .14   | .10  | .72 |             |             |

**p < .001.
Table 2
Reliability Analysis: TechCo Sample

<table>
<thead>
<tr>
<th>Construct</th>
<th>M</th>
<th>SD</th>
<th>Coefficient</th>
<th>95% Confidence Interval of a</th>
<th>Squared Standardized Factor Loading</th>
<th>Coefficient H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absorptive capacity (ACap)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assessment</td>
<td>5.515</td>
<td>0.976</td>
<td>.659</td>
<td>0.606-0.706</td>
<td>.33</td>
<td>.74</td>
</tr>
<tr>
<td>Assimilation</td>
<td>6.052</td>
<td>0.870</td>
<td>.780</td>
<td>0.745-0.810</td>
<td>.79</td>
<td>.85</td>
</tr>
<tr>
<td>Application</td>
<td>6.101</td>
<td>0.918</td>
<td>.833</td>
<td>0.807-0.856</td>
<td>.69</td>
<td>.90</td>
</tr>
<tr>
<td>Experienced community of practice (eCoP)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communication</td>
<td>5.373</td>
<td>0.984</td>
<td>.769</td>
<td>0.733-0.801</td>
<td>.81</td>
<td>.78</td>
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<tr>
<td>Vocabulary</td>
<td>5.107</td>
<td>1.103</td>
<td>.806</td>
<td>0.776-0.883</td>
<td>.90</td>
<td>.82</td>
</tr>
<tr>
<td>Remember</td>
<td>5.180</td>
<td>1.079</td>
<td>.804</td>
<td>0.775-0.832</td>
<td>.69</td>
<td>.83</td>
</tr>
<tr>
<td>Learning</td>
<td>6.184</td>
<td>0.864</td>
<td>.852</td>
<td>0.826-0.870</td>
<td>.27</td>
<td>.88</td>
</tr>
</tbody>
</table>
In an attempt to better understand the results we ran the same analysis using the first order factor model for the three ACap and four eCoP constructs. This model achieved a much better fit of the data to the model, $\chi^2(255) = 799.33, p < .001$, CFI = .97, RMSEA = .06, SRMR = .08. Inspection of the expected paths and modification indices led us to investigate other paths. We decided to estimate the full path coefficient matrix as shown in Table 3. The resulting data fit the model very well, $\chi^2(238) = 727.78, p < .001$, CFI = .97, RMSEA = .06, SRMR = .05. Table 3 shows both the initial (in italics) and modified path coefficients.

These results must be interpreted with great caution as they result from exploratory analyses. However, the results are consistent with the conceptual model of ACap and eCoP. For eCoP we found that all of the path coefficients to SatShare and SatFind from the first-order factors were statistically significant. Only the learning subfacet was statistically significantly related to CoPAttend. The learning subfacet was also statistically significantly related to TechComp. With regard to ACap, all first-order factors were statistically significantly related to CoPAttend. Additionally, assimilate was found to have statistically significant path coefficients with TrnWeeks and SatFind whereas application was statistically significantly related to TechComp and SatShare. The patterns of statistically significant path coefficients are generally consistent with our conceptual model of ACap and eCoP. Future research should develop and specify relationships based on theory and empirical support.

**Evidence of Consistency—Cross-Validation**

For the cross-validation analysis we used the measurement equivalence analytic process followed by Wang and Russell (2005). We estimated hierarchically ordered nested factor models for both ACap and eCoP measures to evaluate the equivalence factor structures across the two samples. Our base model (Model 1) allowed the regression coefficient matrix ($A$), the latent-factor variance–covariance ($\Phi$), and
measurement error variance ($\theta$) matrices to freely vary across samples. In Model 2, we fixed the $\Lambda$ matrices to be invariant across samples. In Model 3, we constrained both the $\Lambda$ and $\Phi$ matrices to be invariant across samples. Finally, in Model 4, we constrained the $\Lambda$, $\Phi$, and $\theta$ matrices to be invariant across samples.

Wang and Russell (2005) made a cogent argument for the use of RMS $\text{ea}$ and its confidence interval to compare nested models noting their nonsensitivity to number of indicators, the number of factors, and sample sizes. In contrast to chi-square statistics that are known to be sensitive to sample size and number of parameters estimated, Cheung and Rensvold (2002) found that $\Delta$RMSEA between two nested models is not affected by sample size and model complexity.

We followed Wang and Russell’s (2005) model using comparisons of 90% RMS $\text{ea}$ confidence intervals to test for differences between nested models. If the RMSEA for a nested model remains within the confidence intervals of RMSEA for the unconstrained model, then the differences in fit of data to the model are not considered statistically significant. A 90% confidence interval of RMSEA provides higher power in detecting differences than a more restrictive 95% confidence interval. Table 4 includes the fit and change statistics comparing the nested models described above. Even though we report both chi-square and RMS $\text{ea}$ indices, like Wang and Russell, we relied on RMS $\text{ea}$ values to judge the fit of data to the model, in recognition that the chi-square statistic’s sensitivity to sample size and that our sample sizes were substantial. The 90% confidence intervals of RMS $\text{ea}$ for each model indicate that the decrement in fit to the model as the parameter matrices are constrained to be invariant between the two samples was not statistically significant, with the exception of Model 4 for the ACap and eCoP measures. For all but this last test, the values of RMSEA remained less than .08 and were within the 90% confidence interval for the nonconstrained model as the models became more constrained, thus supporting the idea that the fit of data to the models are not reliably different.

Our measurement equivalence analyses across groups provided solid evidence that the raw scores on the observed variables can be meaningfully interpreted across the populations. Because the RMSEA for Model 2 fell within the confidence interval for Model 1 on both constructs, the mean raw scores on the observed variables can be meaningfully interpreted across populations. Similarly, the Model 3 RMSEA fell within the confidence interval for Model 1, thus, we can conclude that the factor structures were invariant across these populations. Model 4, which tests for invariance of the reliability of the obtained scores, was a statistically significant difference (at the .10 level of significance) from the unconstrained Model 1 for both ACap and eCoP. Using our conservative test, this model indicated that while the modeled factor structures for both ACap and eCoP were invariant across samples, the scores do not have the same estimated reliability in both samples. However, this finding is not unexpected because of the differences in the job roles and organizational structure
Table 4
Simultaneous Confirmatory Factor Analysis Fit Indices Across Sample 1 \((n = 540, 555)\) and Sample 2 \((n = 231)\) for ACap and eCoP

<table>
<thead>
<tr>
<th>Model Specification Across Samples</th>
<th>df</th>
<th>(\chi^2)</th>
<th>Comparison</th>
<th>(\Delta df)</th>
<th>(\Delta \chi^2)</th>
<th>RMSEA (90% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absorptive capacity (ACap)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1: Free (\Lambda, \Phi, ) and (\theta) matrices</td>
<td>48</td>
<td>201.37*</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0.064 (0.055-0.074)</td>
</tr>
<tr>
<td>Model 2: Fixed (\Lambda) and free (\Phi) and (\theta) matrices</td>
<td>54</td>
<td>240.53*</td>
<td>Model 1 vs. Model 2</td>
<td>6</td>
<td>39.16*</td>
<td>0.067 (0.059-0.076)</td>
</tr>
<tr>
<td>Model 3: Fixed (\Lambda) and (\Phi) and free (\theta) matrices</td>
<td>60</td>
<td>279.11*</td>
<td>Model 2 vs. Model 3</td>
<td>6</td>
<td>38.58*</td>
<td>0.069 (0.061-0.077)</td>
</tr>
<tr>
<td>Model 4: Fixed (\Lambda, \Phi, ) and (\theta) matrices</td>
<td>69</td>
<td>414.63*</td>
<td>Model 3 vs. Model 4</td>
<td>9</td>
<td>135.52*</td>
<td>0.081 (0.073-0.088)</td>
</tr>
<tr>
<td>Experienced community of practice (eCoP)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1: Free (\Lambda, \Phi, ) and (\theta) matrices</td>
<td>96</td>
<td>450.02*</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0.069 (0.062-0.072)</td>
</tr>
<tr>
<td>Model 2: Fixed (\Lambda) and free (\Phi) and (\theta) matrices</td>
<td>104</td>
<td>468.14*</td>
<td>Model 1 vs. Model 2</td>
<td>8</td>
<td>18.12**</td>
<td>0.067 (0.061-0.073)</td>
</tr>
<tr>
<td>Model 3: Fixed (\Lambda) and (\Phi) and free (\theta) matrices</td>
<td>112</td>
<td>549.81*</td>
<td>Model 2 vs. Model 3</td>
<td>8</td>
<td>81.67*</td>
<td>0.071 (0.065-0.077)</td>
</tr>
<tr>
<td>Model 4: Fixed (\Lambda, \Phi, ) and (\theta) matrices</td>
<td>124</td>
<td>787.84*</td>
<td>Model 3 vs. Model 4</td>
<td>12</td>
<td>238.03*</td>
<td>0.083 (0.077-0.088)</td>
</tr>
</tbody>
</table>

Note: \(df\) = degrees of freedom; RMSEA = root mean squared error of approximation; CI = confidence interval. *\(p < .01\). **\(p < .05\).
across the samples (we elaborate on this point in the discussion section). Overall, these results provided strong evidence of measurement structural equivalence of the scales across the two samples.

In addition to the structural evidence of measurement equivalence, the scale scores also demonstrated high coefficient alpha reliability estimates in the R&DCo sample (the TechCo sample is discussed above). The estimated coefficient alphas and their confidence intervals as well as the estimated coefficient $H$s are shown in Table 5.

ACap assessment had a higher coefficient alpha in this sample than in the TechCo sample, whereas the coefficient alpha estimate was lower for the eCoP construct of vocabulary in this sample (based on 95% confidence intervals of alpha for scores on each scale in both samples). This may reflect differences in the two samples’ work roles as well as differences in the specificity and formalization of communities of practice, respectively. However, most of the confidence intervals (except for the vocabulary facet of the eCoP construct) for these estimated coefficient alphas overlap the acceptable range for reliability for research purposes (Henson, 2001; Nunnally & Bernstein, 1994).

**Evidence for Aggregation**

We considered that if eCoP was descriptive of the community of practice to which the respondent is a member, and if ACap reflected the respondent’s work team, there should be some consistency among members of a community of practice in eCoP, and among members of a workgroup in ACap ratings. Table 6 reports the $r_{wg}$ computed for each subscale and overall construct. All $r_{wg}$ estimates were well above the .70 criteria indicating a high degree of agreement within workgroups (for ACap) and within CoPs (for eCoP). In R&DCo there were not uniquely identifiable CoPs. In this context, respondents were members of a variety of CoPs, many of which are outside the firm (e.g., scientific or professional associations) so we were unable to compute $r_{wg}$ estimates for eCoP in the R&DCo sample. Members within workgroups appear to be consistent in their ratings of ACap in both firms, and members within identifiable communities of practice in TechCo are consistent in their rating of eCoP.

**Discussion**

The goal of this study was to design and test two new measures (ACap and eCoP) that could be used in future research on the organizational knowledge transfer ecosystem. We provided a better mapping of constructs and measurement for further research on the broad reaching and possibly symbiotic relationship of different knowledge dynamics in organizations. Results from the confirmatory factor analyses suggested that in our two samples for both the ACap and eCoP measures, our data fit
Table 5
Reliability Analysis: R&DCo Sample

<table>
<thead>
<tr>
<th>Construct</th>
<th>M</th>
<th>SD</th>
<th>Coefficient a</th>
<th>95% Confidence Interval of a</th>
<th>Squared Standardized Factor Loading</th>
<th>Coefficient H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absorptive capacity (ACap)(^a)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assessment</td>
<td>5.33</td>
<td>1.03</td>
<td>.839</td>
<td>0.800-0.872</td>
<td>.75</td>
<td>.86</td>
</tr>
<tr>
<td>Assimilation</td>
<td>5.36</td>
<td>0.93</td>
<td>.845</td>
<td>0.807-0.877</td>
<td>.98</td>
<td>.87</td>
</tr>
<tr>
<td>Application</td>
<td>5.13</td>
<td>1.05</td>
<td>.870</td>
<td>0.838-0.897</td>
<td>.79</td>
<td>.92</td>
</tr>
<tr>
<td>Experienced community of practice (eCoP)(^b)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communication</td>
<td>5.80</td>
<td>1.22</td>
<td>.938</td>
<td>0.922-0.950</td>
<td>.36</td>
<td>.94</td>
</tr>
<tr>
<td>Vocabulary</td>
<td>4.82</td>
<td>1.03</td>
<td>.641</td>
<td>0.552-0.714</td>
<td>.12</td>
<td>.68</td>
</tr>
<tr>
<td>Remember</td>
<td>5.50</td>
<td>1.01</td>
<td>.859</td>
<td>0.824-0.888</td>
<td>.76</td>
<td>.90</td>
</tr>
<tr>
<td>Learning</td>
<td>5.79</td>
<td>0.97</td>
<td>.902</td>
<td>0.878-0.922</td>
<td>.89</td>
<td>.91</td>
</tr>
</tbody>
</table>

a. \(\chi^2(24) = 28.74; p > .05\); comparative fit index [CFI] = .99; root mean squared error of approximation [RMSEA] = .03; standardized root mean square residual [SRMR] = .03. b. \(\chi^2(50) = 135.59; p < .001\); CFI = .93; RMSEA = .09; SRMR = .10.
Furthermore, the constructs yielded coefficient alphas and coefficient $H_s$ that were mostly greater than .80, which is generally considered a guideline for acceptable construct reliability for research purposes (Henson, 2001; Nunnally & Bernstein, 1994). We also found partial support for the criterion that we thought would be theoretically related to the two constructs. Additionally, from our measurement equivalence analyses across samples, we found evidence that the raw scores on observed variables for both scales can be meaningfully interpreted across the populations (comparing Models 1 and 2) and the factor structures for both scales were invariant across these populations (comparing Models 2 and 3). In contrast, we did not find support for residual invariance across samples (comparing Models 3 and 4), which indicates the reliability of both ACap and eCoP scale scores are sensitive between our two populations.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Mean $r_{wg}$</th>
<th>Var $r_{wg}$</th>
<th>$N$ Groups</th>
<th>$N$ Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experienced community of practice</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(eCoP): TechCo sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>eCoP composite</td>
<td>0.960</td>
<td>0.001</td>
<td>14</td>
<td>329</td>
</tr>
<tr>
<td>Communication</td>
<td>0.853</td>
<td>0.002</td>
<td>14</td>
<td>329</td>
</tr>
<tr>
<td>Vocabulary</td>
<td>0.807</td>
<td>0.002</td>
<td>14</td>
<td>329</td>
</tr>
<tr>
<td>Remember</td>
<td>0.821</td>
<td>0.003</td>
<td>14</td>
<td>329</td>
</tr>
<tr>
<td>Learning</td>
<td>0.927</td>
<td>0.001</td>
<td>14</td>
<td>329</td>
</tr>
<tr>
<td>Absorptive capacity (ACap): TechCo</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACap composite</td>
<td>0.938</td>
<td>0.014</td>
<td>83</td>
<td>311</td>
</tr>
<tr>
<td>Assessment</td>
<td>0.793</td>
<td>0.052</td>
<td>83</td>
<td>311</td>
</tr>
<tr>
<td>Assimilation</td>
<td>0.876</td>
<td>0.029</td>
<td>83</td>
<td>311</td>
</tr>
<tr>
<td>Application</td>
<td>0.880</td>
<td>0.019</td>
<td>83</td>
<td>311</td>
</tr>
<tr>
<td>Absorptive capacity (ACap): R&amp;DCo</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACap composite</td>
<td>0.965</td>
<td>0.003</td>
<td>42</td>
<td>231</td>
</tr>
<tr>
<td>Assessment</td>
<td>0.865</td>
<td>0.008</td>
<td>42</td>
<td>231</td>
</tr>
<tr>
<td>Assimilation</td>
<td>0.891</td>
<td>0.001</td>
<td>42</td>
<td>231</td>
</tr>
<tr>
<td>Application</td>
<td>0.965</td>
<td>0.002</td>
<td>42</td>
<td>231</td>
</tr>
</tbody>
</table>

a. $N$ groups for eCoP is the number of uniquely identified communities of practice within TechCo. R&DCo does not have uniquely identifiable communities of practice, thus aggregation within CoPs is not possible. $N$ groups for ACap equals the number of distinct workgroups with at least three members reporting. b. $N$ respondents is reduced from the total sample because some workgroups were represented by only one or two respondents, and some individuals could not be uniquely identified with a specific community of practice.
This result for eCoP is not surprising. In fact, there is good reason for why the fully constrained model did not fit as well. For eCoP, the primary difference is that in TechCo the CoPs were formally defined and clearly identifiable, had a steady membership, and the CoPs had distinct domains of knowledge. In contrast, in R&DCo, the CoPs were not formally or clearly defined, membership was very fluid, and the CoPs ranged widely in the degree of specificity of knowledge. Furthermore, comparing the coefficient alphas table for the two populations (Tables 3 and 5), it appears that the subdimension of vocabulary is differently interpreted in R&DCo than in TechCo. This can be attributed to the fluid nature of eCoPs in R&DCo, where the constant turnover of members may not allow members a long enough time together to establish a common vocabulary or lingo. Because eCoP scores were shown by the above analysis to have different reliability estimates across samples, and from what we know about the different organizations, we can conclude that informal and widely varying CoPs may lead to different interpretations of the component constructs than more formal and specific CoPs.

Differences in the populations regarding the A Cap measure may be attributed to the way the sampled teams were organized. For example, in TechCo, the TARs were situated in teams, but they were often regionally dispersed with limited team member interaction. The TARs often worked more directly with account managers (not other TARs), and therefore the idea of assessment of information may differ because of their isolation from other TARs on their team. In contrast, the engineers and scientists in R&DCo worked more collaboratively within their groups and interacted on a more frequent basis. It may be that the difference between the coefficient alphas on the sub-dimension of assessment is due to sensitivity around the different ways the work teams are organized. This idea is supported when comparing the intergroup agreement on the subdimension of assessment across TechCo and R&DCo in Table 5, where TechCo intergroup agreement is lower and has a greater variance than R&DCo. Thus, even though we observed statistically significant differences between the two groups when constraining the error variances across samples, this was expected because of the differences explained above.

Although clearly the results of our path analysis must be interpreted with great caution as they result from exploratory procedures, there is some evidence that the new measures correlate with other related measures in explainable ways, providing some criterion-related evidence of validity. We constructed the measures to yield valid scores on the basis of content evidence (i.e., developers and reviewers see clear relations between the item content and the theoretical constructs) and are appropriate to our goal of having brief, concise measures to aid field research. The components of A Cap and eCoP function as related components critical to knowledge transfer in organizations. The confirmatory factor analyses showed significant benefit to considering the measures separately, as we theorized. Furthermore,
aggregation statistics indicated a high level of agreement among respondents within a workgroup (on ACap) and within communities of practice (eCoP) supporting the reliability of these scores for describing the conditions within workgroups and communities of practice, respectively. Future research using a multilevel approach using these two constructs could provide insight into how these measures have differential influence depending on the level of analysis. These new measures will allow for more fine-grained measurement than was possible in the past and for the ability to consider these dimensions of the knowledge ecosystem in concert with one another.

Appendix

Absorptive Capacity (ACap)

Assessment
acap.1: People in my team are able to decipher the knowledge that will be most valuable to us.
acap.2: It is easy to decide what information will be most useful in meeting our customer’s needs.
acap.3: We know enough about the technology we use to determine what new information is credible and trustworthy.

Assimilation
acap.4: The shared knowledge within my team makes it easy to understand new material presented within our technical areas.
acap.5: It is easy to see the connections among the pieces of knowledge held jointly within our team.
acap.6: Many of the new technological developments coming to the team fit well into the current technology.

Application
acap.7: It is easy to adapt our work to make use of the new technical knowledge made available to us.
acap.8: New technical knowledge can be quickly applied to our work.
acap.9: My customers can immediately benefit from new technical knowledge learned in the team.

Experienced Community of Practice (eCoP)

Open Communication
cop.1: I feel comfortable communicating freely with others in my technical specialty.

(continued)
Appendix (continued)

cop.2: In my technical specialty there is an open environment for free communication.
cop.3: It is easy to communicate with others in my technical specialty.

*Shared Vocabulary*

cop.4: My technical specialty has a unique vocabulary.
cop.5: There is a common understanding within my technical specialty of the words and meanings that are used within the technical specialty.
cop.6: People outside my technical specialty might have difficulty understanding the vocabulary members of my technical specialty use to talk about the technology.

*Remembering Previous Lessons*

cop.7: Collaborating with other members of my technical specialty helps me remember things that we have learned.
cop.8: Participating in meetings with members of my technical specialty helps me to remember things that we have learned.
cop.9: Lessons learned from past experiences shared within my technical specialty are easily remembered.

*Learning From Each Other*

cop.10: I interact with others in my technical specialty with the intention of learning from them.
cop.11: I learn new skills and knowledge from collaborating with others in my technical specialty.
cop.12: Learning is shared among members of my technical specialty.

Acknowledgments

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References


Barnette, J. J. (2000). Effects of stem and Likert response option reversals on internal consistency: If you feel the need, there is a better alternative to using those negatively worded stems. *Educational and Psychological Measurement, 60*, 361-370.


