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Team Mental Models of Expertise Location: Validation of a Field Survey Measure

Thomas Ellwart[1], Udo Konradt[2], and Oliver Rack[3]

Abstract

This research provides and validates a field survey measure of team mental models (TMMs) on the location of team member expertise. The measure integrates two important aspects into the expertise location TMM Index: (a) the quality of meta-knowledge about experts within the team, and (b) team consensus regarding within-team expertise. Complementary to content-specific TMM approaches, this measure can be applied across different team and task types as a screening indicator in organizational surveys. To validate the TMM Index, an experimental study (n = 120, 40 teams) and a longitudinal field study (n = 130, 37 teams) were conducted. Both studies provide evidence that the TMM Index is a reliable screening indicator that corresponds to content-specific accuracy and consensus scores. Multilevel analyses revealed that the TMM Index predicts team performance (self- and other ratings), team coordination, and individual variables such as knowledge credibility and self-efficacy over time.

Keywords

team cognition, team mental models, transactive memory systems, performance

[1]University of Trier, Germany
[2]University of Kiel, Germany
[3]University of Applied Sciences Northwestern Switzerland, Olten, Switzerland

Corresponding Author:
Thomas Ellwart, University of Trier, Universitaetsring 15, Trier, D-54296, Germany.
Email: ellwart@uni-trier.de

Knowledge and skills of team members are essential prerequisites for numerous team processes and outcomes, including team functioning, team development, and team performance (Kozlowski & Chao, 2012). Team members' individual expertise refers to "specialized skills and knowledge individuals bring to the team's task" (Faraj & Sproull, 2000, p. 1555). In addition and complementary to individual expertise, the understanding of "who knows what in the team" is another important perspective and key focus of this article. The knowledge about how expertise is distributed within the team or *knowledge about expertise location* is defined as a meta-knowledge about the variety of potentially useful expertise sources in terms of other team members' knowledge and skills (Faraj & Sproull, 2000). Past research demonstrated positive effects of high quality knowledge on expertise location, both on individual- and team-level processes (e.g., Austin, 2003; Ellwart, Buendgens, & Rack, 2014; Hollingshead, 1998). However, outside the lab, the measurement of expertise location on the team level is lacking valid and economic measurement scales for the organizational context. Thus, this article aims to develop and validate a field measure that helps to evaluate and to improve this type of team knowledge in field settings.

A prominent theory to represent knowledge about expertise location refers to team mental models (TMMs), which are collectively shared mental representations of key elements of the team's relevant environment (Klimoski & Mohammed, 1994). Empirical studies have shown positive relationships between TMM and different outcome variables (for overviews, see DeChurch & Mesmer-Magnus, 2010a, 2010b; Mohammed, Ferzandi, & Hamilton, 2010). TMMs are broadly categorized into two content domains: (a) taskwork mental models referring, for example, to shared knowledge about tools, strategies, or plans; and (b) teamwork mental models referring, for example, to shared knowledge about teammates' skills or interaction requirements (Cannon-Bowers, Salas, & Converse, 1993; Mohammed et al., 2010). For the purpose of this study, we speak about *TMMs of expertise location* that belong to the specific content domain of teamwork mental models, and current literature underlines the added value of operationalizing specific content domains in TMM research (Mohammed et al., 2010; Rentsch & Mot, 2012). To operationalize TMM of expertise location, we differentiate between the two aspects of (a) *quality* of knowledge and (b) *consensus* as the degree of sharedness between the team member perceptions. Thus, team members not only need to know who is expert in the team (quality of knowledge), there must also be consensus about the expertise location among the team members.

TMM research has suggested several methods, processes, and tools to capture TMMs, which differ in content, structure, and accuracy (DeChurch & Mesmer-Magnus, 2010b; Ellwart, Biemann, & Rack, 2011; Mohammed et al., 2010). Although existing TMM measures capture the team's cognitions thoroughly, they nevertheless have some limitations. First, most of the current TMM measures are context dependent in nature (Lewis, 2003; Rentsch & Mot, 2012) and, therefore, "need to be tailored to the specific task under investigation" (Mohammed et al., 2010, p. 890). However, organizational teams hardly ever work on tasks comprising straightforward domain-specific characteristics as duties and team responsibilities typically vary across teams (Ellwart et al., 2011; Lewis, 2003). As a consequence, TMM measures on expertise location cannot be compared across teams. Second, because available measures require that the specific domain(s) of expertise be examined in a lengthy and time-consuming analysis of knowledge, it might prevent organizations from using them. For example, in applications such as organizational change settings (Burke, 2011) or in action research (Chin, Benne, & Bennis, 1985), numerous teams are surveyed to monitor or provide feedback on team processes and states. As a consequence, most measures are used in experimental and controlled settings, although deficits in knowledge of expertise location by early screening measures might be highly valuable.

In this article, we propose and validate a measure of TMM of expertise location—the TMM Index. Most previous measures only reflect whether there is consensus among the team members' mental model (high vs. low), but ignored whether team members have an elaborate mental representation (i.e., high consensus in not knowing vs. high consensus in knowing). Thus, the TMM Index of expertise location integrates the quality of the members' knowledge of within-team experts (meta-knowledge of expertise location), and the team's consensus on perceived expertise location within a single coefficient. By providing a measure that is task and team independent, applicable across diverse teams, and easily employed, this research contributes to both team cognition research and to managerial practice. Furthermore, this measure also adds to TMM research by referencing TMM not in a generic or abstract way (Mohammed et al., 2010) but in the specific content domain of team members' knowledge about expertise location. In two studies, we provide evidence to support our assumptions. Study 1 was constructed to show that the TMM Index is a sensitive and accurate indicator of knowledge of expertise location and team consensus. Study 2 examined the predictive validity of the TMM Index in organizational teams over time in a field setting.

Knowing Who Knows What: Knowledge of Within-Team Expertise Location

TMMs of Expertise Location

Within the broad label of team cognition (Salas & Fiore, 2004; Salas, Fiore, & Letsky, 2012), the concept of TMMs (DeChurch & Mesmer-Magnus, 2010a, 2010b; Mohammed et al., 2010) describes the shared, organized understanding of knowledge relevant to key elements of the team (teamwork mental models) and its task(s) (taskwork mental models; Cannon-Bowers et al., 1993; Klimoski & Mohammed, 1994).[1] It is important to note that task-work and teamwork mental models are generic categories (Mohammed, Tesler, & Hamilton, 2012), and researchers need to specify the knowledge domain of interest. While taskwork mental models refer to characteristics of the team's work, major task duties, equipment, and resources, teamwork mental models include features of how team members interact and about their roles, responsibilities, and knowledge domains, which facilitate team interactions to accomplish team goals (Marks, Zaccaro, & Mathieu, 2000; Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). Following this categorization, the knowledge about the location of expertise belongs to the category of teamwork mental models and represents a more precise conceptualization and operationalization of TMM. Thus, TMM of expertise location represents a specific type of TMM, and as recommended by Mohammed et al. (2012), they move away from the abstract content domains of TMM while acknowledging their multifaceted nature and complexity (see Table 1).

Following the identification of the content domain, the type of sharing of this knowledge represents a further major property of TMM (Mohammed et al., 2010; Rentsch & Mot, 2012). In TMM research, indices of sharedness indicate how the individual team members share the knowledge of interest (Mathieu, Heffner, Goodwin, Cannon-Bowers, & Salas, 2005). In addition, various forms of sharedness are distinguished in TMM research. For example, perceptual approaches measure the quality of the TMM content (e.g., level/quality of knowledge about expertise location most often measured by rating scales) and focus on the teams' consensus in terms of within-group agreement. Alternatively, structural approaches focus on within-team similarity or accuracy of cognitive team structures (e.g., representations of specific team experts and their areas of expertise) by modeling how specific contents are organized in the participant's mind (Mohammed et al., 2010; Rentsch & Mot, 2012). Thus, different forms of sharedness indicators result in different types of methodology and measurement (Rentsch & Mot, 2012).

In this article, the TMM measure will be perceptual in nature, quantifying (a) the quality of the members' knowledge of within-team experts (expertise location) and (b) the team's consensus on perceived expertise location into one TMM Index. This perceptual approach, based on rating scales, will not allow identification of the structure and accuracy of a TMM. However, as Rentsch and Mot (2012) point out, the perceptual versus structural approach "traded off information about content or structure in favor of the other and both are lacking to some degree" (p. 150). In this vein, our approach does not

Table 1. Means, Standard Deviations, and Intercorrelations in Studies 1 and 2.

Variable: Study 1	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. TMM Index	3.71	1.31	**.92**									
2. Task-specific consensus	.49	0.22	.62**	—								
3. Task-specific accuracy	3.23	1.55	.67**	.77**	—							
4. Coordination: Self-ratings	5.95	0.84	.18	.10	.31*	**.89**						
5. Coordination: Messages	9.77	2.64	−.46**	−.31*	−.36*	−.08	—					
6. Performance: Time	32.21	6.25	.07	.21	.19	.12	.11	—				
7. Performance: Quality	1.65	0.35	−.12	−.19	.06	−.09	−.04	−.16	—			
8. Performance: Self-ratings	5.58	0.75	.32**	.12	.29†	.65**	−.31*	.18	.02	**.93**		
9. Knowledge credibility	6.05	0.68	.40**	.29†	.48**	.82**	−.31*	.13	−.19	.63**	**.92**	
10. Self-efficacy	5.24	0.63	.28†	.10	.27†	.30†	−.29†	.25	−.25	.46**	.42**	**.85**

Variable: Study 2	*M*	*SD*	1	2	3	4	5	6	7	8
1. TMM Index (T1)	3.37	0.79	**.92**							
2. Task-specific consensus (T1)	.62	0.11	.50**	—						
3. Task-specific accuracy (T1)	2.05	0.33	.45**	.35†	—					
4. Coordination: Self-ratings (T2)	3.76	0.54	.46**	.43*	.08	**.84**				
5. Performance: Self-ratings (T2)	3.98	0.56	.44**	.12	−.09	.66**	**.81**			
6. Performance: Tutor ratings (T2)	3.76	0.80	.31†	.14	−.04	.17	.26	**.83**		
7. Knowledge credibility	4.07	0.48	.49**	.45*	−.06	.75**	.59**	.17	**.91**	
8. Self-efficacy	3.82	0.39	.41**	.04	.13	.37*	.54**	.21	.34*	**.83**

Note. Study 1 (n = 40 teams), Study 2 (n = 37 teams). Task-specific consensus and accuracy are calculated according to Austin (2003); T1 = early phase of the project in Study 2; T2 = later phase of the project in Study 2. For scales, coefficient alpha is printed in boldface type in the diagonal. Significances are reported two-tailed.

†$p < .10$. *$p < .05$. **$p < .01$.

rule out the structural measures of TMM for application and research but rather serves as a complement because it is applicable for specific context situations and samples.

Measurement of TMM of Expertise Location in Field Settings

As pointed out above, this article aims to develop a measure of TMM on expertise location that can be applied in field settings as a first indicator or screening about the quality and the consensus of the teams' knowledge about expertise location. The applied setting and sample focused on here require that the following characteristics are met. First, the measure does not depend on a specific team or task and can be applied across settings independently from the specific areas of expertise within the teams surveyed. Second, because screening measures often serve the purpose of initial data collection in change processes and are often applied in the context of larger surveys (Burke, 2011), the measure developed in this study was designed to require a low investment of resources (time and effort) for its completion. Third, in contrast to the existing measures of individual knowledge about expertise location (e.g., Faraj & Sproull, 2000), the TMM measure has to capture the quality of knowledge about expertise location as well as the consensus on it at the team level. However, most of the measurement approaches of TMM have been successfully applied in highly standardized experimental and task-specific settings (e.g., Cooke, Salas, Cannon-Bowers, & Stout, 2000; DeChurch & Mesmer-Magnus, 2010b; Ellwart et al., 2011; Langan-Fox, Code, & Langfield-Smith, 2000; Mohammed et al., 2010; Mohammed, Klimoski, & Rentsch, 2000), underlining the importance of methods that are applicable for research in the field context.

To assess TMM, two methodological approaches can be distinguished: structure- and perception-oriented measures (Cooke et al., 2000; DeChurch & Mesmer-Magnus, 2010b; Langan-Fox et al., 2000; Mohammed et al., 2010; Mohammed et al., 2000; see also Table 1).

Structure-Oriented Measures

The first methodological approach focuses on the analysis of the structure between various elements of the TMM by attempting to measure the pattern of knowledge arrangement. Structured cognition is often assessed using techniques such as pathfinder networks (Stout, Cannon-Bowers, Salas, & Milanovich, 1999), UCINET (Mathieu et al., 2005), concept mapping

(Marks, Sabella, Burke, & Zaccaro, 2002), and multidimensional scaling (cf. Cooke et al., 2000; Mohammed et al., 2000). Researchers ask for information about how team members relate specific concepts of knowledge to each other (e.g., expert A is related to knowledge Y but less related to knowledge X); these comparisons are transferred statistically into indicators of similarity. The overlap or agreement of individual structures indicates whether team members have a similar "network of concepts in mind" (Rentsch & Mot, 2012, p. 151). A second indicator of structural methods is accuracy. As Rentsch and Mot (2012) explain, accurate structured "cognitions exist to the extent cognitions match a target" (p. 151). In this vein, accuracy depends on the comparison with a correct structured model, and researchers have to identify in advance the perfect structure to which the TMM are to be compared.

Overall, the emphasis of structured TMM is on the recognition, structural relation, and accuracy of specific concepts. Transferred to the measurement of expertise location in the field, specific domains of expertise would have to be determined prior to the measurement, which hinders the early application as a screening instrument across various types of teams and task types. Moreover, structural TMM do not operationalize the degree with which team members describe the quality or level of a specific concept (e.g., how much knowledge about an expertise location exists). This focus on the quality of perceptions and its sharedness is operationalized in perceptual conceptualizations of TMM.

Perception-Oriented Measures

The second methodological approach is focused on beliefs or perceptions of team members (DeChurch & Mesmer-Magnus, 2010b).[2] As proposed by Rentsch, Small, and Hanges (2008), this approach will not afford an understanding of explanatory relations. Using Likert-type scales, researchers measure two forms of perceptual information: (a) quality in terms of the mean group perception (e.g., do all team members know the specific expertise of each other) and (b) consensus between the ratings of the team members (Rentsch & Mot, 2012). In early studies, indices are based on the concept of within-group agreement (e.g., r_{WG}, see James, Demaree, & Wolf, 1984) and are used to derive TMM agreement (e.g., Eby, Meade, Parisi, & Douthitt, 1999; Levesque, Wilson, & Wholey, 2001; Webber, Chen, Payne, Marsh, & Zaccaro, 2000). However, there are strong limitations and problems in interpreting the value of r_{WG} -related computations (magnitude of the r_{WG} depends on scale anchors and sample size; negative values are set at zero; see Brown & Hauenstein, 2005). Transferred to our research, the perceptual approach can be applied in the field across different types of teams and tasks. Imagine, for instance, a survey item such as "In your team, do you know who possesses specific expertise?" Agreement indices within each team would serve as indicator of consensus (i.e., degree to which all members share the same quality of knowing team experts). However, it remains unclear whether agreement or disagreement was in knowing the experts (high level or good quality of knowledge) or not knowing the experts (low level or quality of knowledge) because agreement measures ignore information about the mean level of the ratings. Because of this limitation, the approach developed in this article integrates quality and consensus into one perceptual TMM Index.

Operationalization and Validation of the TMM Index of Expertise Location

To assess this variable, we adopted Faraj and Sproull's (2000) measure because it represented a validated field measure with a focus on expertise location. Originally, this measure reflects, from a team-level perspective, whether the team has knowledge about the experts within the team. Because of its group-focused survey wording, the items do not mirror individual representation of each member's knowledge (cf. Klein, Conn, Smith, & Sorra, 2001). Thus, the original items were changed to an individual wording perspective.[3] From this perspective, the measure captures the quality of individual meta-knowledge about expertise location (e.g., Ellwart et al., 2011; Ellwart & Konradt, 2007; Srivastava, Bartol, & Locke, 2006). For reasons of simplicity, in the remaining part of the article, the term *meta-knowledge* will be used to refer to the quality of knowledge about expertise location.

Following the idea of TMM, we argue that consensus on individual expertise perceptions is a team phenomenon related to a specific type of perceptual TMM (cf. Cannon-Bowers et al., 1993; DeChurch & Mesmer-Magnus, 2010b; Mohammed et al., 2010). Consensus is conceptualized as the extent of agreement on perceptions of expertise location within the team (Rentsch & Mot, 2012). To calculate the degree of consensus of the individual scores at the team level, we used the average deviation (AD) score (Burke & Dunlap, 2002; Burke, Finkelstein, & Dusig, 1999). Compared with the r_{WG}-related indices applied as the agreement score in the early studies on TMM (e.g., Eby et al., 1999; Levesque et al., 2001; Webber et al., 2000), the AD overcomes the shortcomings of the r_{WG} (e.g., scale dependency, interpretation of negative values, assumption of a null distribution as agreement; see Brown & Hauenstein, 2005, for an overview).[4] As the aim of the TMM Index of expertise location is to integrate individual knowledge and team consensus into a single score, the AD score is subtracted from the mean score to provide information about the team members' knowledge of expertise location in relation to the degree of consensus within the team.

This type of TMM measure is clearly perceptual in nature (Rentsch & Mot, 2012) and has the advantage of screening a very specific domain of team cognition while demanding only little time and effort of respondents. However, the screening approach will neither reveal the underlying structure of the representation of team expertises (who exactly is the expert in specific domains) to researchers and practitioners nor indicate whether the perceptions are accurate. This information requires more elaborated techniques such as structural measures. The value of this specific TMM Index is its practicability as an early screening measure independent of the specific tasks or team characteristics. Moreover, in the context of change and action research (Burke, 2011), it offers a first insight into the teams' cognitions within the framework of large-scale surveys and identifies those units which are of interest for further structural diagnoses of TMMs.

To provide validity of this approach, the TMM Index of expertise location should be sensitive to (a) team differences regarding high and low quality of knowledge about the experts in the team, and (b) high and low team consensus on this perception. Thus, this perceptual TMM Index must relate to the objective underlying knowledge about team experts and its consensus among team members. If the underlying knowledge about team experts and its consensus among team members is experimentally manipulated in ad hoc teams (by creating different expertise domains and forming different heights of consensus about the perception of expertise), the TMM Index would yield validity when it can differentiate between these experimentally generated conditions. This experimental validation allows creating teams with high versus low qualities of knowledge about expertise location as well as groups with high versus low consensus. The newly developed measure should be able to identify the manipulated condition. In a field setting, validation depends on the given variance of TMM in given groups and requires intensive team and task analysis to objectively identify the knowledge and consensus about specific team experts and their domains of expertise. Thus, in Study 1, knowledge and consensus about expertise location was experimentally manipulated between groups to test the sensitivity of the TMM Index toward the objective underlying knowledge structure. Specifically, it was proposed,

> **Hypothesis 1:** The TMM Index differentiates between teams with high knowledge and high consensus (highest indices) versus high knowledge and low consensus as well as between teams with low knowledge and low consensus and low knowledge and high consensus (lowest indices).

The TMM Index of expertise location reflects team members' general perceptions on whether they have knowledge of team members' expertise and skills and whether there is consensus about this perception within the team. To prove content validity, the task-unspecific perception in the TMM Index (e.g., "I know which team members have expertise in specific areas") should relate to measures that capture accuracy and consensus of perception in a task-specific way by identifying and naming experts and their related expertise domains. Austin (2003) proposed an elaborate method to capture task-specific accuracy and consensus of expertise location. Each team member would identify and name one expert of several task-specific areas (e.g., statistics, writing). These named experts are then compared and integrated into a team consensus score. Moreover, each participant would rate his or her own expertise in the mentioned areas, offering the possibility to calculate accuracy scores on whether members identified themselves as an expert in the same areas (for details, see Austin, 2003). A clear indication of content validity of our task and team independent TMM Index of expertise location would be provided if it corresponds with the accuracy and consensus from task-specific direct expertise ratings. Consequently, we propose,

Hypothesis 2a: The TMM Index is positively related to task-specific accuracy scores from expertise ratings.
Hypothesis 2b: The TMM Index is positively related to task-specific consensus scores from expertise ratings.

It is obvious that accuracy and consensus ratings by team members depend on the validity of the self-evaluation of the experts and may be biased in some ways. For this reason, Hypothesis 1 was formulated to test the sensitivity of the TMM Index related to the experimentally manipulated objective knowledge structure in the groups, and Hypotheses 2 was designed to compare the task-unspecific TMM Index with task- and team-specific evaluations of expertise domains.

The TMM Index of expertise location should also be positively related to team process and outcome variables proposed in the research on TMM and transactive memory systems (DeChurch & Mesmer-Magnus, 2010a; Mohammed et al., 2010). On the team level, pertinent research has shown that shared knowledge about the location of expertise within the team improves coordination and performance compared with teams with little consensus and meta-knowledge (e.g., Austin, 2003; Levesque et al., 2001; Lewis, 2003). Coordination as an outcome represents the extent to which team members have managed interdependencies to varying degrees of success (Espinosa, Lerch, & Kraut, 2004; Hoegl & Gemuenden, 2001). At the team level, the mental models of expertise location should be positively related to team coordination (Lewis, 2003) because the TMM allows team members to integrate knowledge, ask questions, and search for missing knowledge in an efficient fashion (Moreland & Myaskovsky, 2000). The concept of TMM was initially developed to explain performance differences between groups (Mohammed et al., 2010), and studies with perceptual and structural TMM showed the positive relationships with different performance indicators (DeChurch & Mesmer-Magnus, 2010b). Indicators for performance are heterogenic and reach from scoring points in experimental tasks, decision quality, efficiency, or satisfaction (Kozlowski & Ilgen, 2006; Mohammed et al., 2010). Thus, we propose on the team level,

> **Hypothesis 3a:** The TMM Index of expertise location is positively related to coordination success.
> **Hypothesis 3b:** The TMM Index of expertise location is positively related to team performance.

High quality and consensus of knowledge about the teams' experts will also affect the individual team member in her or his task-related thinking and behavior. Recent work showed positive effects of TMM contents on individual variables such as members' trustworthiness (Chou, Wang, Wang, Huang, & Cheng, 2008). Specifically, the TMM on expertise location should increase the team members' trust to rely on the expertise of others (i.e., knowledge credibility; Lewis, 2003). Moreover, when team members know who to ask in difficult situations and are aware of their own expertise roles, the personal beliefs to have the ability and the resources to perform the task well (self-efficacy) will also increase (Bandura, 1977, 1997; Peterson, Mitchell, Thompson, & Burr, 2000). Thus, we propose on the individual level,

> **Hypothesis 4a:** Team members in teams with high TMM Index will exhibit higher scores of knowledge credibility.
> **Hypothesis 4b:** Team members in teams with high TMM Index will exhibit higher scores of task-related self-efficacy.

Two studies were conducted to test the validity of the TMM Index of expertise location. In Study 1, quality (meta-knowledge) and team consensus on expertise location were experimentally manipulated. The aim was to provide evidence that the TMM Index is a sensitive and valid indicator of TMMs of expertise location, and that the TMM Index relates to individual-and team-related outcome variables. The experimental manipulation allows controlling the objective knowledge allocation and recognition as well as consensus on within-team location of expertise to test the sensitivity of the index. Identical scales and measurement approaches of the first study were applied in the longitudinal field study (Study 2). The goal of Study 2 was to show that the TMM Index is a valid measure for survey research that predicts individual- and team-level outcomes of ongoing teams over time.

Study 1

Method

Sample. One hundred twenty undergraduate students (30 males and 90 females, *M* age = 24 years, *SD* = 6.1 years) were recruited from a large German public university to participate for course credit. Participants worked in three-person teams, and the composition of the teams did not differ significantly with regard to sex and age (*F*s < 1, *ns*).

Procedure and design. In Study 1, the objective amount of individual meta-knowledge about team experts was varied in a way that mirrors how teams may differ in the level of knowing the team experts (high and low meta-knowledge) as well as in the consensus of this perception (high and low consensus). Accordingly, a team task was developed which was based on the idea of the hidden profile paradigm (Stasser, 1992; Stasser, Stewart, & Wittenbaum, 1995) because of the advantage it offers to manipulate high and low levels of knowledge and team consensus in a 2 × 2 experimental design. Knowledge about the expertise location in the team was systematically varied between the experimental teams of three participants who were assigned to solve a decision-making task. Participants, who were randomly assigned to the teams, were told that they worked in a company that analyzes weather information to recommend one of three travel routes to their customers. Each member received a specific customer request regarding three possible travel routes, each consisting of three stations. Based on weather criteria given by the customers (e.g., customer 1: warm, dry, calm weather for swimming; customer 2: mild, dry, windy weather for sailing), each team member had to decide which of the three routes was best suited to the customers' wishes. Although the customer requests differed for each team member, the team worked and made decisions using the identical weather information. However, to create interdependence between the team members, relevant weather information from the weather domains was distributed between domain experts (e.g., expert for wind, temperature, or rain). Each expert had all information about the specific weather domain at all stations along the routes. To gather the missing information from the other experts, participants had the chance to exchange information. Thus, each team member had to solve the task individually but needed information from the other experts (resource interdependence; cf. Wageman, 1995). The task had a correct solution for each customer request based on the best combination of customers' conditions and the actual weather situation for each route and station.

In the resulting 2 × 2 experimental design, four experimental groups were tested: (a) teams with high quality of knowledge about expertise location (meta-knowledge) and high team consensus (all participants knew that each member received information about the expertise domains of each other team member); (b) teams with low meta-knowledge and high consensus (no one received information about the expertise of the other team members and all were told that no one else received this information either); (c) teams with high meta-knowledge and low consensus (two participants received information about the expertise within the team but no one was given information about what other team members were/were not told); and (d) teams with low meta-knowledge and high consensus (only one of the three team members received expertise information but all were informed that only one member received said information and were told which member). Thus, meta-knowledge and consensus in the team depended both on the distribution of expertise and the accuracy of knowledge of location of expertise.

Each group had to solve two sets of three customer requests in two subsequent tasks. Although content and weather conditions changed between the tasks, the expertise domains did not. At the start of the first request, participants received instructions and information about expertise (depending on the experimental manipulation). Following the manipulation check, each participant worked on the specific task to determine what information was missing. To document the questioning procedure for missing information, and to provide data with which coordination costs could be operationalized, each team member was asked to write a simulated email to the team members. Emails were either addressed to all members representing high coordination costs versus addressed to specific team members representing low coordination costs. After completion of the email task, missing information was personally exchanged among the group participants in face-to-face meetings, and participants finished the first request and completed the items of the TMM Index measure (predictor at T1). This was followed by objective expertise ratings (see Austin, 2003) where participants named the experts of the different weather domains and rated their own expertise. Then, participants worked on the second set of customer requests, and the information exchange followed. Finally, participants completed questionnaires on coordination success, team performance, knowledge credibility, and self-efficacy at the end of the experimental session (criteria at T2).

TMM Index. This measure was adopted from Faraj and Sproull (2000; see also Ellwart et al., 2014; Srivastava et al., 2006) and consisted of four items ("I have a good 'map' of other team members' talents and skills," "I know which team members have expertise in specific areas," "I know what task-related skills and knowledge each team member possesses," and "I know who on the team has specialized skills and knowledge that are relevant to me"). All items of the TMM Index of expertise location, perceived performance, coordination success, knowledge credibility, and self-efficacy were measured using a 7-point rating measure ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Cronbach's alpha = .92. To calculate consensus, AD scores for all items of the measure were computed (Burke et al., 1999). This represents the mean average absolute deviation divided by the group mean of each item. Finally, AD scores were averaged for the whole measure (cf. Burke et al., 1999). To calculate the TMM Index, AD was subtracted from the teams' mean score of the measure.

Task-specific consensus and accuracy. For the validation of the TMM Index, task-specific consensus and accuracy scores were calculated based on the identification of each expert and experimental assignment (cf. Austin, 2003). Each team member had to name who was the team expert for each of the six domains (e.g., condensation, cloudiness, wind, air temperature, humidity, and visibility). Teams whose members identified the same individual as an expert on a given domain were considered to have high task consensus. Standard deviation scores were calculated to measure team member consensus of expert identification for each domain. Finally, domain consensus scores were combined to a single mean consensus score for the team. Thereby, a higher score indicated higher team consensus.

Accuracy was measured by combining experimentally assigned expertise and team members' objective expertise ratings of expertise location. If the identified experts concurred with the assigned expertise, team's accuracy is considered high. Individual-level perceived expertise accuracy scores were averaged to the team level to create the team accuracy score (for details on the computation, see Austin, 2003).

Coordination. Good coordination is given when members can efficiently ask questions and search for missing knowledge (Moreland & Myaskovsky, 2000). Email messages formulated in response to the task of documenting the questioning procedure for missing information were used to assess coordination. The emails could be addressed either to all members or to a specific person in the team. Participants were instructed to communicate, in a clear and brief manner, only task-relevant information (questions about weather conditions). The total number of emails each team member would have to answer during a task represented coordination costs. Perceived coordination success was measured at the end of the experimental session with a four-item measure from Lewis (2003; for example, "Our team works together in a well-coordinated fashion."). Cronbach's alpha = .89. Previous research has demonstrated that the measure shows good psychometric properties (Ellwart & Konradt, 2007; Lewis, 2003).

Team performance. Team performance was measured quantitatively using the time needed to solve the final task and the correct decision for the travel route. In addition, perceived qualitative team effectiveness was measured at the end of the experimental session by a three-item measure adopted from Hoegl and Gemuenden (2001; for example, "The project result was of high quality") and aggregated at the group level. Cronbach's alpha = .93.

Knowledge credibility. On the individual level, perceived knowledge credibility was measured at the end of the experimental session with four items from Lewis (2003; for example, "I'm confident relying on the information that other team members brought to the discussion"). As in previous research (Ellwart & Konradt, 2007; Lewis, 2003), the measure demonstrated good reliability. Cronbach's alpha = .92.

Self-efficacy. Self-efficacy was measured on the individual level with three items from Hertel, Konradt, and Orlikowski (2004) at the end of the experimental session (e.g., "I feel capable of accomplishing the tasks within my team"). There have been numerous applications of this scale in past research that have demonstrated good reliability and validity (e.g., Ellwart & Konradt, 2007; Geister, Konradt, & Hertel, 2006; Hertel, Deter, & Konradt, 2003).

Control variables. We also acknowledged the potential role of other factors that can influence behaviors in teams such as previous acquaintance, which can contribute to level (rate and effectiveness) of team members' communication. Therefore, we included acquaintance of the participants into the data analyses (e.g., Kozlowski & Bell, 2003). Acquaintance was measured with three items asking whether participants (a) have worked together in previous student projects, (b) have jointly participated in leisure time activities, and (c) are/were close friends. Cronbach's alpha = .73.

Analyses. For analyses on the team level, we used linear regression. To examine whether aggregation was appropriate, intraclass correlation coefficient [ICC(2)] values were first calculated (i.e., indexes of interrater agreement;

Shrout & Fleiss, 1979). ICC(2) values relating to the perceived coordination (.98) and the perceived performance (.97) were adequate indicating suitable levels of agreement (Glick, 1985). Further support for aggregation was provided by r_{WG} coefficients (James et al., 1984). The r_{WG} values for perceived coordination and perceived team performance were .75 and .72, respectively, representing satisfactory agreement (George, 1990; James et al., 1984). Finally, we calculated ICC(1) values (Shrout & Fleiss, 1979). ICC(1) values relating to perceived coordination ICC(1), .88, $F(39, 429) = 8.33$, $p < .01$, and perceived performance ICC(1), .79, $F(39, 312) = 4.64$, $p < .01$, were well above the median level of ICC(1) reported in the organizational literature (James et al., 1984). Together, these data provide sufficient justification for aggregation of the individual-level measures to the team level.

Hierarchical linear modeling (HLM) was used to predict individual-level outcomes such as credibility and self-efficacy (Raudenbush & Bryk, 2002). HLM allows a simultaneous examination of the effects of variables at both individual and team levels, as well as possible cross-level interaction effects (Raudenbush & Bryk, 2002). Following the recommended procedure for HLM analysis (Hofmann, 1997; Raudenbush & Bryk, 2002), we first assessed within- and between-team variance in the dependent variable (null model). If significant variance in individual variables between teams was found, an intercept as outcome model was estimated (Hofmann, 1997). This model estimates whether the variance in the individual variables is significantly related to the TMM of expertise location (Level 2 predictor). Acquaintance was included into the model as an additional Level 2 control variable. Because the individuals (Level 1) are not only nested in teams (Level 2) but teams are also nested in the experimental condition, we modeled the experimental groups at Level 3 to control for the nested data structure. HLM analyses also provided a multiparameter test for the variance–covariance components to compare the deviance statistic of the null model with the intercept-as-outcome model. This comparison offers information when the addition of Level 2 indicators has a significant contribution to the explanation of variation in the outcome. Because the predictors were measured after completion of task one and the outcomes (e.g., objective expertise ratings) at the end of the experiment, problems with common method variance were of no concern here (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Results

Means, standard deviations, and bivariate correlations are presented in Table 1. To test whether the TMM Index is sensitive to team differences regarding high and low levels of meta-knowledge and consensus about the location of

Table 2. Means, Standard Deviations, and Within-Group Agreement of Experimentally Manipulated Meta-Knowledge and Consensus of Four Experimental Groups in Study 1.

	Low meta-knowledge		High meta-knowledge	
Variable	Low consensus	High consensus	Low consensus	High consensus
Mean meta-knowledge	4.37 (.93)	4.05 (.73)	4.78 (.93)	5.88 (.66)
Average deviation (consensus about meta-knowledge)	1.36 (.41)	.95 (.40)	1.23 (.48)	0.70 (.21)
r_{WG} Meta-knowledge	.19	.61	.36	.87
TMM Index expertise location	3.01 (0.98)	3.09 (1.01)	3.54 (0.97)	5.18 (0.79)

expertise (Hypothesis 1), we first compared experimental teams regarding their TMM Index of expertise location. Table 2 shows mean team score of expertise location, AD, and TMM Index for all experimental groups. In addition, the r_{WG} score for the TMM items is also displayed. Results from ANOVA indicate that the mean team score, $F(3, 36) = 9.34$, $p < .001$, $\eta^2 = .44$, AD, $F(3, 36) = 5.71$, $p < .01$, $\eta^2 = .32$, and TMM Index, $F(3, 36) = 10.11$, $p < .001$, $\eta^2 = .46$, significantly differ between teams. Moreover, when comparing teams with high consensus and low consensus, the TMM Index differs significantly, $t(38) = 2.17$, $p < .05$. Similarly, the TMM Index is sensitive to teams with high versus low meta-knowledge, $t(38) = 3.62$, $p < .001$. As shown in Table 2, r_{WG} agreement mirrors the manipulated differences regarding high versus low consensus. Thus, Hypothesis 1was supported.

To validate the TMM Index (Hypotheses 2), we related the TMM Index to task-specific accuracy and consensus scores following the procedure from Austin (2003). As shown in Table 1, the TMM Index relates to the team consensus score, $r = .62$, $p < .001$, as well to accuracy, $r = .67$, $p < .001$, and provides support for Hypotheses 2a and 2b. Thus, comparing the impersonal ratings of the TMM Index with task- and team-specific naming of team experts according to Austin (2003), teams with high meta-knowledge and consensus show much higher agreement and accuracy in naming domain experts.

Table 3. Regression Results for TMM Index and Group-Level Controls.

	Study 1			Study 2		
Step/variable	Coordination: Self-ratings	Coordination: Messages	Performance: Self-ratings	Coordination: Self-ratings	Performance: Self-ratings	Performance: Tutor ratings
1 Team size				.07	.25	.38*
1 Acquaintance	.10	.20	−.02	−.35†	−.16	−.18
2 TMM Index	.21	−.47**	.39**	.64**	.54**	.44*
F	1.25	4.99**	3.32*	4.48**	3.61*	3.13*
R^2	.06	.21	.15	.29	.25	.22
Adjusted R^2	.01	.17	.11	.23	.18	.15
n	40	40	40	37	37	37

Note. Standardized regression coefficients are reported. Significances are reported two-tailed.
†$p < .10$. *$p < .05$. **$p < .01$.

As predicted in Hypotheses 3a and 3b, group-level TMM Index of within-team expertise location should predict team coordination (Hypothesis 3a) as well as team effectiveness (Hypothesis 3b).[5] Results of hierarchical regression analyses are presented in Table 3.[6] Controlled for previous acquaintance, team's TMM Index predicts coordination costs, represented by number of received emails, $\beta = -.47$, $p < .01$. In teams with high meta-knowledge and consensus, team members show less coordination costs than teams with low TMM Index scores. Similarly, our data show that TMM Index predicts performance self-ratings, $\beta = .39$, $p < .01$, but not performance time, quality, and perceived coordination efficacy. Thus, Hypothesis 3b received only partial support.

As shown in Table 4, HLM indicated that the TMM Index of the team can explain variance in knowledge credibility and self-efficacy on an individual level (Hypotheses 4a and 4b). In a first step, the null model indicates that there is significant variance for knowledge credibility and self-efficacy between groups. In the intercept-as-outcome model, TMM Index and acquaintance are entered into the regression. For individual knowledge credibility (Hypothesis 4a), previous acquaintance, $\beta = .46$, $p < .01$, and TMM Index of expertise location, $\beta = .18$, $p < .01$, explain significant amounts of variance for this individual variable. Deviance statistics (χ^2 model comparison) indicate that TMM Index and acquaintance make a significant contribution to the explanation of variation in the outcome. Thus, controlled by previous acquaintance, high meta-knowledge and consensus in a team predict individual trust in the knowledge and skills of fellow team members. For self-efficacy (Hypothesis 4b), the TMM Index also explains between-group variance in the one-tailed test, $\beta = .12$, $p < .05$.

Table 4. Multilevel Regression Results for TMM Index and Individual-Level Variables.

Step/variable	Study 1		Study 2	
	Knowledge credibility	Self-efficacy	Knowledge credibility	Self-efficacy
1 Team size			−.04	.04
1 Acquaintance	.47**	−.05	−.09	−.15†
2 TMM Index	.18**	.10**	.28**	.26**
ICC (null model)	.29**	.04	.16*	.12†
ICC (Model 1)	.08	.03	.02	.01
χ^2 (model comparison)	5.47*	1.77	10.2*	9.4*

Note. Final estimation of Level 2 regression coefficients on Level 1 intercepts are reported. Significances are reported two-tailed.
†$p < .10$. *$p < .05$. **$p < .01$.

Discussion of Study 1

Study 1 yielded initial support for the hypothesis that the TMM Index on expertise location is a sensitive indicator of the objectively manipulated within-team expertise location and team consensus. Moreover, the TMM Index relates to the team members' task-specific team consensus and accuracy scores determined from explicit participant ratings of all team members. On the group level, analysis yielded significant effects of the TMM Index on coordination variables and perceived team effectiveness, but not on team performance. There are different explanations for the missing effects on performance in this controlled laboratory setting. First, the number of subjects in this experimental setting is typically lower compared with field settings resulting in the lack of power to detect possible effects. Moreover, from a methodological perspective, the samples in experiments are typically more homogeneous compared with non-experimental studies which reduce the variance in the groups. Finally, performance in the experimental situation was operationalized by the solution of the hidden profile. Because the task was artificial with little complexity compared with field tasks, participants were easily able to solve the task. This floor effect is probably also responsible for the fact that participants subjectively perceived coordination as good, thus leading to missing effects on this variable as well. However, HLM indicated that the TMM Index of the team explains variance for knowledge credibility well and marginally for self-efficacy on the individual level. This finding is important because it provides a valid and applicable survey measurement approach of within-team expertise location.

In this study, the TMM Index was experimentally manipulated to test the reliability and validity of the survey measure and its relationship with team and individual outcomes. In Study 2, we tested the generalizability of the results of Study 1 and conducted a replication study within a different context using a longitudinal field sample.

Study 2

The goal of Study 2 was to show that the TMM Index of expertise location predicts individual- and group-level outcomes in an applied field setting. Although Study 2 is correlational in nature, separate times for the assessment of predictor and criteria variables reduces biases of common method variance (Podsakoff et al., 2003) and allows for better interpretations compared with single-point cross-sectional designs.

Method

Sample. Participants in Study 2 were 130 students (105 females and 25 males; *M* age = 24 years, *SD* = 5.0) recruited from a large university in Germany. Organized into 37 teams, they worked together in an undergraduate course over a period of 3 months to gain course credit. All teams worked on a small-scale research project on developing, conducting, and evaluating a scientific research question assisted by a course tutor. The areas of expertise were literature search, test planning, data collection, statistical analyses, as well as oral and written presentation of the results. Team size ranged from three to five members (*M* = 3.4, *SD* = 0.8).

Procedure. Student teams were assessed in an early (T1) and later (T2) phase of the project. Following a typology by King and Cleland (1988), the teams worked in the T1 conceptual and definition phase (about 2 weeks after team start), evaluating objectives and strategies and determining schedule, performance, and resource requirements. At T2 (about 10 weeks after team start), teams were in their operational phase, collecting data or working on analyses and presentations.

Measures. To ensure comparability, we used the same measures as in Study 1. For Study 2, Cronbach's alpha was .92 for TMM Index, .84 for coordination, .91 for knowledge credibility, .83 for self-efficacy, and .81 for aggregated team performance. TMM Index as well as accuracy and consensus ratings were measured at T1. Knowledge credibility, self-efficacy, perceived coordination success as well as performance (self- and tutor ratings) were measured at T2.

Task-specific consensus and accuracy ratings. For validation of the TMM Index, consensus and accuracy scores were again calculated based on team members' explicit identification of within-team experts and their expertise domain self-ratings. Prior interviews with the team instructors revealed six domains of expertise closely related to the students' projects: coordination/organization, theory/literature, task planning, statistics, written reports, and oral presentation. Objective consensus was calculated by measuring team consensus on who was the team expert for each of the six domains. Teams whose members identified the same individual as an expert on a given domain were considered to have high task consensus. The calculation was identical to Study 1 (cf. Austin, 2003).

Task-specific accuracy was measured by combining self- and team members' identifications of expertise. Accuracy was determined by matching team member identification of experts with self-report ratings of expertise. The more the identified experts concurred with the team member (i.e., they rated themselves as experts in that domain), the higher the team accuracy rating was. Following Austin (2003), the accuracy measure was calculated by first determining separate scores of expertise accuracy for each team member. Expertise accuracy was determined by matching team member identification of expertise with self-report ratings of member expertise. This individual-level perceived expertise accuracy score was averaged to the team level to create the team accuracy score (for details on the computation, see Austin, 2003). High team accuracy indicates that team members correctly identified the experts who considered themselves as experts in a particular area.

Team performance. In addition to performance self-ratings aggregated at the team level, team performance was also evaluated by the tutor. Each instructor rated how the team performed using the measure by Hoegl and Gemuenden (2001). Cronbach's alpha = .83.

Control variables. Acquaintance (M = .98, SD = 0.58) and team size (M = 3.32, SD = 0.98) may contribute to the level of an outcome (e.g., Kozlowski & Bell, 2003) and were used as controls. Acquaintance was measured with the same three items used in Study 1.

Analyses. Similar to Study 1, we applied linear regression for team-level prediction. To examine whether aggregation was appropriate, first ICC(2) values were calculated (i.e., indexes of interrater agreement; Shrout & Fleiss, 1979). ICC(2) values relating to the perceived coordination (.94) and the perceived performance (.95) were adequate, indicating suitable levels of agreement (Glick, 1985). Further support for aggregation was provided by r_{WG} coefficients (James et al., 1984). The r_{WG} values for perceived coordination and perceived team performance were .74 and .76, respectively, representing satisfactory agreement (George, 1990; James et al., 1984). Finally, we calculated ICC(1) values (Shrout & Fleiss, 1979). ICC(1) values relating to perceived coordination ICC(1), .88, $F(36, 396) = 8.02$, $p < .01$, and perceived performance ICC(1), .85, $F(36, 288) = 6.87$, $p < .01$, were well above the median level of ICC(1) reported in the organizational literature (James et al., 1984). Together, these data provide ample justification for aggregation of the individual-level measures to the team level. HLM was applied for predicting credibility and self-efficacy.

Results

Means, standard deviations, and bivariate correlations are presented in Table 1. Descriptive statistics indicate that teams differ with regard to meta-knowledge and consensus. Reported meta-knowledge ranges from 1.38 to 4.67 ($M = 3.46$, $SD = 0.78$). Most interesting, AD of the reported meta-knowledge ranged from .13 to .88 ($M = 0.48$, $SD = 0.19$). Transferred to r_{WG} scores, interrater agreement regarding meta-knowledge is .74 ($SD = 0.16$) across all teams, with 13 teams (35%) below the threshold of .70. This indicates that consensus about the expertise location varies between teams as a phenomenon of TMM.

To validate the TMM Index in the field sample (Hypotheses 2a and 2b), we related the TMM Index on T1 to task-specific accuracy and consensus scores (T1) following Austin (2003). These scores are based on self- and other ratings of all team members on six specific domains of expertise. As suggested in Hypothesis 2a, the TMM Index relates to the team consensus score, $r = .50$, $p < .01$, as well as to accuracy as suggested in Hypothesis 2b, $r = .45$, $p < .01$. Table 1 displays the results. Thus, teams with TMM indices of high meta-knowledge and consensus show more agreement and accuracy in naming the correct experts for different task domains.

Hypotheses 3a and 3b, predicting that group-level TMM Index of expertise location on T1 should predict team's coordination success (Hypothesis 3a) as well as team's effectiveness (Hypothesis 3b) in the later phase of the project (T2), were supported. Results from hierarchical regression analyses are presented in Table 3. Controlled for previous acquaintance and team size, team's TMM Index predicts perceived coordination, $\beta = .64$, $p < .01$, as well as team performance perceived by team members, $\beta = .54$, $p < .01$, and the tutor, $\beta = .44$, $p < .01$. Teams with high TMM indices of expertise location in the beginning of the project (T1) report better coordination and performance during the operational phase assessed at T2.

To test Hypotheses 4, individual-level outcomes on T2 were analyzed by HLM. Intraclass correlations (ICC) indicate significant variance between teams regarding knowledge credibility and self-efficacy. In the intercept-as-outcome model, acquaintance, team size, and TMM Index are entered into the regression (see Table 4). Predicting knowledge credibility, the TMM Index of expertise location, $\beta = .28$, $p < .01$, can explain variance for this individual variable (Hypothesis 4a). Controlled for acquaintance and team size, high meta-knowledge and consensus in a team predicts individual trust in the knowledge and skills of the team members. For self-efficacy (Hypothesis 4b), the TMM Index significantly explains group variance, $\beta = .26$, $p < .01$. Thus, in teams with high meta-knowledge and consensus about expertise location, team members feel capable of accomplishing the team tasks. Deviance statistics for both regressions indicate that the TMM Index contributes significantly to the explanation of variation in the outcome.

Discussion of Study 2

Study 2 reassessed and replicated the findings from Study 1 in a longitudinal field setting using student project teams. Results showed that the TMM Index again was related to task-specific consensus and accuracy scores from transactive memory research (Austin, 2003). Thus, the TMM Index represents an effective and short method to screen teams' meta-knowledge and consensus. Moreover, TMM indices assessed 3 weeks after team start predicted perceived team coordination and performance, both rated by the responsible tutor and the team members, respectively. Finally, results from HLM showed that the TMM Index can explain knowledge credibility and self-efficacy on the individual level.

General Discussion

The aim of this article was to provide and validate a field screening measure that integrates (a) the quality of knowledge about the experts within the team (meta-knowledge) and (b) the team's consensus on within-team expertise into one TMM Index. First and foremost, this measure should be applicable across different types of teams and tasks in organizational surveys and should confirm relationships with outcome variables such as teams' effectiveness and attitudes. Results from our experimental study (Study 1) and field study

(Study 2) clearly demonstrate that the TMM Index is a valid measure of expertise location in teams. In the experimental study, meta-knowledge about expertise location and consensus was objectively manipulated within each team. The TMM Index was able to differentiate between these teams. This gives support that both the dimensions of meta-knowledge and consensus are two relevant aspects of TMM that can be represented in one index. In both studies, the TMM Index was able to predict relevant variables on the team and individual level. As suggested, the TMM Index also predicted team coordination success (Lewis, 2003) and team performance (Mohammed et al., 2010). Using multilevel analyses, the TMM Index predicted individual trust in the knowledge of the teammates (knowledge credibility; Lewis, 2003) and self-efficacy (Peterson et al., 2000). The empirical data support the assumption that the TMM Index is a conceptually and statistically valid measure of meta-knowledge and consensus about the location of expertise within teams. However, the task-independent characteristics of the measure make it appropriate for field settings and allow comparisons between different teams and tasks in organizational change settings or action research (Burke, 2011). Convergent and criterion-related validity was shown through its relationship to established task-specific measures of accuracy and consensus introduced by Austin (2003).

From a methodological perspective, Study 1 was an experimental manipulation of meta-knowledge and consensus, whereas Study 2 focused on field data. Most importantly, the experimental manipulation in Study 1 allowed controlling the objective meta-knowledge and consensus about the location of within-team expertise to verify the sensitivity of the index. Study 2 was designed to replicate these findings in a field setting. The advantage of testing the TMM Index in both a field application and in a controlled laboratory experiment is that the strengths of one method can, to some extent, compensate for the weaknesses of the other. The strengths of Study 1 include the fact that the structure of team knowledge of within-team expertise location was controlled and a link toward outcomes was supported. The added value of Study 2 is that the replication of these outcomes in multiple team settings demonstrates generalizability. An obvious weakness is its correlational nature. However, by measuring predictors and criteria at different times, the overestimation of the relationships between variables and influence of common method biases could be reduced in both studies (Podsakoff et al., 2003). Moreover, specific analyses of participants' task-specific ratings on team experts, identification of their own expertise, and consequent accuracy ratings indicated construct validity. A second methodological advantage can be found in the application of multilevel analyses. Variables such as knowledge credibility and self-efficacy are outcomes on the individual level, whereas the shared mental model index of expertise location is a group-level variable. To comply with the nested data, HLM was used to predict individual-level variables (Raudenbush & Bryk, 2002). In sum, the fact that the validity of the TMM Index of within-team expertise location was supported across methodologies provides valuable support for the argument that this measure is a useful screening approach for assessing expertise location in teams.

Value of the TMM Index of Expertise Location for Organizational Surveys

A major aim and advantage of the TMM Index is its task- and team-independent practicability, for example, in field settings as a first indicator or screening about the quality and the consensus of the teams' knowledge about expertise location. Although various measures of team knowledge have been introduced in recent years (cf. Cooke et al., 2000; DeChurch & Mesmer-Magnus, 2010b; Langan-Fox et al., 2000; Mohammed et al., 2010), there is a clear lack of measures that are suitable for application in the field (Lewis, 2003; Rentsch & Mot, 2012).

In the present contribution, we defined three characteristics of the TMM Index: First, the measure does not depend on a specific team or task and can be applied across settings, independent of the specific areas of expertise within the teams surveyed. Second, the measure requires a low investment of resources (time and effort) for administration. Third, the TMM measure captures the quality of knowledge about expertise location as well as the consensus about it on a team level.

Existing methods from research on TMM (e.g., pathfinder networks, UCINET, concept mapping) are excellent tools for research in a controlled and well-defined research setting to measure the underlying structure of team cognition. However, applications with regard to expertise location would rely on a clear a priori definition of all possible areas the team has expertise to handle and of the expertise domains of all team members. During measurement, participants would have to rate a priori defined expertise domains versus concepts in an elaborate way. Such approaches are not practicable for the settings of early team screenings because of the effort and complexity to determine domains of expertise across different teams or organizations. Moreover, it is difficult to convince field partners to apply such time-consuming measurement approaches, especially in the early phases of projects. Perceptual measures of TMM based on agreement indices derived from questionnaires consisting of Likert-type scales are suitable (e.g., Eby et al., 1999; Levesque et al., 2001; Webber et al., 2000) but only offer an indicator of consensus. However, this indicator does not reveal whether the level of agreement is associated with knowing versus not knowing the experts. With the TMM Index of within-team expertise location, both the quality of knowledge about expertise location and team consensus are integrated into a single index. For this reason, the TMM Index of expertise location offers an economic screening measurement approach that can be used across various team and task types. Although the TMM Index cannot capture the specific underlying organizational structure of the specific knowledge domains, it is clearly related to objective team- and task-specific ratings and can be used as a screening tool prior to more extensive investigations of specific teams. Thus, the TMM Index is a valuable alternative for many field applications in organizations where laborious and complex methods to assess knowledge and consensus are difficult to apply. The application may be practically oriented, for example, in organizational change settings (Burke, 2011), or research oriented in generating and explaining theoretical models of TMM. For example, present research on TMM explores the mechanisms of team learning or leadership and discusses TMM as a cognitive mediator in explaining team performance (Wiedow, Konradt, Ellwart, & Steenfatt, in press; DeChurch & Mesmer-Magnus, 2010a).

Limitations

There are some limitations to the methodological aspects of these two studies as well as some shortcomings of the TMM Index. The first limitation is that both studies were conducted with student participants, which casts some measure of doubt on the robustness of the results. However, the second study was done with students who participated in actual teams that were assigned objectives to accomplish to gain course credits. Moreover, Ellwart et al. (2014) applied the same version of a within-team expertise location scale from Faraj and Sproull (2000) and found similar effects on knowledge exchange and identification. They allowed a reanalysis of their data by computing the TMM Index following the procedure applied in this study. Their field data from 73 organizational teams reveal correlations of the TMM Index on expertise location (data from team members) with supervisor ratings of team knowledge exchange ($r = .21$, $p < .07$; three-item scale by Ellwart & Konradt, 2007) and innovation behavior ($r = .24$, $p < .04$; three-item scale by Jannsen, 2000).[7] Although these results suggest the potential of the TMM Index in organizational settings, future research should examine its validity across different in situ jobs and organizations.

Second, notwithstanding the advantages of the TMM Index of within-team expertise location to integrate knowledge and consensus into a single measure, the size of the index is represented by a linear transformation of the difference between meta-knowledge and the consensus. High scores indicate high agreement on existing meta-knowledge, whereas low scores indicate less meta-knowledge and agreement. Although results in Study 1 indicate the sensitivity of the index to both dimensions, research might be useful regarding the separate effects and interactions of both indicators. Similar to a study by Bliese and Halverson (1998) on team consensus and psychological well-being, one could conceive of a regression approach entering the main effects of meta-knowledge, consensus, and finally, the interaction term. This would offer researchers valuable information on the incremental impact of each dimension on team or individual variables. However, there are some statistical and practical shortcomings. From a statistical point of view, consensus and meta-knowledge might be highly correlated in field situations, leading to multicollinearity of the predictors, thus forcing the researcher to combine the variable. From an applied perspective, practitioners apply the TMM Index to determine where knowledge about within-team expertise is lacking in organization teams. If the index indicates teams with relative deficits in the knowledge about team experts, further assessments and team development programs can follow. In the present studies, it was of less interest to illustrate what main effect or interaction could explain a model, as the present imperative was to demonstrate the index as a valid predictor of team performance. Given that this was shown in both studies, the single index has been validated as a practicable and valuable tool.

Third, the linear transformation between knowledge and consensus (AD) offers further lines of research. In the present state, meta-knowledge and AD are weighted equally in the same metric (Burke & Dunlap, 2002), assuming that AD and absolute meta-knowledge have a similar impact on the TMM. It would be of conceptual and practical interest to investigate whether a higher impact of consensus or meta-knowledge leads to better predictions of performance. For example, if consensus is the crucial variable for some team tasks, one could enlarge the impact of the AD by enhancing the impact of AD on the TMM Index. Further research may be worthwhile to examine the effects of different weights on performance indices in simulation studies to optimize the predictive validity of the TMM Index.

A final point addresses the limitation of the TMM Index compared with the structural measures applied in TMM research. This perceptual measure operationalizes the content of cognition but not the degree of structural similarity of the mental representation (Rentsch & Mot, 2012). Because of its disregard of the structural dimension, Mohammed et al. (2010) would argue that this Likert-type–based approach is not a TMM measurement technique in its own right, whereas others would classify the approach as a TMM elicitation method compared with the structural assessment of TMM (DeChurch & Mesmer-Magnus, 2010b). In sum, both the perceptual and the structural approach tap into the content of TMMs (Rentsch & Mot, 2012), but in doing so, they draw complementary pictures of team cognition. In this vein, the perceptional approach of the TMM Index developed in this article does not rule out the structural measures of TMM for application and research but rather serves as a complement to such measures because it is applicable for specific context situations and samples.

Conclusion

We conclude that the TMM Index is useful to screen TMM about expertise location in field settings and across a variety of team types and tasks. The measure, which integrates consensus scores and means ratings into a single predictive index, could—due to its brevity—easily be applied in other content domains of TMM research and may be a lucrative topic of further investigations. For example, task-relevant knowledge could be measured by asking team members whether they know about the goals and/or strategies of the team. As a first screening indicator, the TMM Index gives researchers and practitioners helpful initial insights into team cognition but requires deeper and more elaborated subsequent analyses to get a complete picture of team mental representations.

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Notes

1. In the literature, there are several terms referring to team mental models (TMMs) such as teamwork mental models, shared mental model, shared cognition, team cognition, team member schema similarity. Related to the concept of TMM of expertise location is the conceptualization of transactive memory systems (Hollingshead, Gupta, Yoon, & Brandon, 2012' Wegner, 1986, 1995).There are two similarities between transactive memory systems and TMM of expertise location: First, the content domain of knowledge about expertise within the team and second, the sharedness of this knowledge in terms of the agreement. However, transactive memory systems are not TMM; rather they go further, as

they explain "how people in collectives learn, store, use, and coordinate their knowledge" (Hollingshead et al., 2012, p. 421). In this regard, Mohammed, Ferzandi, and Hamilton (2010) classify transactive memory systems as taskwork knowledge, whereas TMM of expertise location focus on the skills and knowledge of the team members (teamwork TMM). For a comprehensive review, see also DeChurch and Mesmer-Magnus (2010b). Besides the group-level phenomenon of TMM of expertise location, the concept of expertise recognition is also discussed as a characteristic of individual team members. There is evidence from experimental social psychological as well as from applied field research that individual recognition of fellow team members' expertise is important for group decision making and team performance (Ellwart, Buendgens, & Rack, 2014; Faraj & Sproull, 2000; Littlepage & Mueller, 1997; Stasser, Stewart, & Wittenbaum, 1995).

2. Perceptual measures operationalize the content of cognition but not the degree of structural similarity of the mental representation (Rentsch & Mot, 2012). Because of neglect of the structural dimension, some authors argue that the Likert-type–based approaches do not constitute a TMM measurement technique in its own right (Mohammed et al., 2010), whereas others would classify perceptual approaches as TMM elicitation methods (DeChurch & Mesmer-Magnus, 2010b). For the goal of initial screening, the approach is valuable because the Likert-type–based approach allows developing a task- and team-independent measure. However, this type of measure only represents a first elicitation of the TMM of organizational groups; for examining the structure and accuracy in-depth, detailed structural methods are necessary.
3. The adopted items were tested and validated in a previous study by Ellwart and Konradt (2007). They were translated from the original scale by Faraj and Sproull (2000), following the forward–backward procedure proposed by Brislin (1980) to arrive at conceptual equivalence.
4. For estimating consensus in the proposed TMM Index, the average deviation (AD) has two major advantages. First, AD indices do not require the determination of a null random response distribution as for r_{WG}, which is the primary determinant of the quality of the agreement estimate. Second, AD is computed relative to the mean of an item and thus provides direct conceptualizations in the same metric of the original measure (Burke & Dunlap, 2002). The same metric allows relating the team consensus scores on expertise location (AD) to the team members' mean level of knowledge of expertise location in one single coefficient, which we denote as the TMM Index.
5. A check for distributional assumptions of maximum likelihood estimation reveals that univariate and multivariate skewness and kurtosis were within acceptable range (cf. Tabachnick & Fidell, 2001).
6. Although the validation focuses on the regression between the TMM Index and the outcomes, the teams analyzed in the regression are nested in experimental groups. To respect the nested structure of the data, we performed hierarchical linear modeling (HLM) analyses between TMM Index and team outcomes by

modeling the experimental groups as upper level variable. The results of HLM are comparable with simple regressions displayed in Table 3. Additional HLM analyses are available on request. We wish to thank the reviewers for the advice concerning the nested structure.
7. We appreciate the permission granted to apply the TMM Index to these data.

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Author Biographies

Thomas Ellwart is a full professor in business psychology at the University of Trier, Germany. His current research interests include diversity in teams, team mental models, and team learning.

Udo Konradt holds a PhD in psychology and is a full professor of work, organizational and consumer psychology at the University of Kiel, Germany. His research interests include virtual teams and virtual collaboration, IT usage and usability, and team learning.

Oliver Rack holds a PhD in psychology and is a professor of organizational psychology at the University of Applied Sciences and Arts Northwestern Switzerland, School of Applied Psychology. His research interests include interaction processes in computer-mediated groups, team mental models, and the management of distributed collaboration.