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PERFORMANCE BENEFITS OF RECIPROCAL VICARIOUS LEARNING IN TEAMS

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Team members' vicarious learning from other members' knowledge and experience is a critical component of learning and performance in interdependent team work contexts. Yet, our understanding of vicarious learning among individuals in teams is still quite limited, as this learning is often oversimplified (as one-way knowledge-sharing) or aggregated (as a collective, team-level property), resulting in incomplete and inconsistent findings. In this paper, I extend these views by exploring the underlying distribution of dyadic vicarious learning relationships in teams, specifically using a network approach to examine the consequences of *reciprocity* in team members' vicarious learning with one another (i.e., where both individuals in a given dyad learn vicariously from each other's knowledge and experience). Using a novel method for calculating weighted reciprocity in networks in a study of MBA consulting project teams, I demonstrate that greater team vicarious learning reciprocity is associated with greater team performance, and also moderates the performance consequences of teams' external learning efforts, offering a potential reconciliation of conflicting results in prior research. In doing so, this paper advances research on vicarious learning in teams, while also providing conceptual and empirical tools for studying learning and other interpersonal workplace interactions from a network perspective.

As work tasks, and the expertise required to perform them, become increasingly interdependent and distributed among members of cross-functional teams in organizations, successful performance requires individuals to effectively learn from and integrate the knowledge and experience shared by other team members (Edmondson, Dillon, & Roloff, 2007). This *vicarious learning* among team members—defined as an individual's learning from a process of absorbing and interpreting another's knowledge and experiences in order to expand their repertoire of responses for future tasks or performance challenges (Myers, 2018)—forms a core component of team learning (Argote & Gino, 2009), reflecting how individuals share, receive, and integrate knowledge and experiences in their respective networks of relationships with others in the team (e.g., Glynn, Lant, & Milliken, 1994).

Yet, prior research has tended to present an overly simplified view of vicarious learning at work, often building from an assumption, for instance, that this learning is unidirectional—that there is a "sharer" of knowledge and a "learner" who receives the knowledge, and that these roles are stable within a learning relationship (implicitly assuming that a "sharer" would never learn from the "learner"). This assumption can be seen in the tendency for prior work to examine *either* what might drive a person (often an expert team member) to share knowledge with someone (e.g., a novice team member) *or* what leads to the seeking of knowledge by these more novice members from experts (e.g., Hofmann, Lei, & Grant, 2009; Levin & Cross, 2004; Osterloh & Frey, 2000). By focusing on only a knowledge sharer or recipient, these studies have implicitly committed to the "one-way" learning assumption, as they have made *ex ante* conceptual and empirical determinations of individuals' roles—for instance, equating "expert" with "sharer"

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and "novice" with "learner or recipient." This is a potentially troublesome simplification, because when individuals learn vicariously from others they do not simply "consume" a sharer's experience (Matzler & Mueller, 2011: 318) but rather often "feed back questions, amplifications, and modifications that add further value" (Quinn, Anderson, & Finkelstein, 1996: 8), helping to motivate a "mutual give-and-take" of knowledge (Ipe, 2003: 346). As a result, our understanding of these vicarious learning relationships among individuals at work, and particularly the consequences of different distributions of these dyadic relationships among members of a group or team, is still quite limited (see Myers, 2018).

In this paper I aim to broaden our understanding of vicarious learning by examining the consequences of differing levels of *reciprocity* in team members' vicarious learning relationships (i.e., the extent to which person A learns from the experiences and insight shared by person B, and B in turn learns from those shared by A). In contrast to the prevailing one-way assumption described above, reciprocity may be a particularly relevant characteristic of team members' learning relationships, as the cross-functional, interdependent team contexts increasingly found in organizations offer significant opportunities for bidirectional learning among peers on the team. Indeed, reciprocity has been identified as a feature of workplace learning, with evidence indicating that considerations of reciprocity play a part in motivating greater engagement in knowledge-sharing among organizational units (e.g., Dyer & Nobeoka, 2000; Schulz, 2001), as well as explaining patterns of advice-seeking among teachers (Siciliano, 2016). Building on this nascent recognition of reciprocity's role in workplace learning, I hypothesize and test the performance consequences of more reciprocal vicarious learning in teams. Using a sample of MBA consulting project teams, I find empirical support for a direct effect of vicarious learning reciprocity on team performance, as well as a moderating effect of this reciprocity in explaining the performance benefits (or costs) of teams engaging in external learning.

Advancing a model of vicarious learning reciprocity in teams offers several key contributions to studies of teams and learning in modern organizations. First, in contrast to earlier team research that has focused on stable, collective attributes of teams (i.e., relying on aggregated, static team-level constructs to explain outcomes), I contribute to a growing body of research that has used a network approach to explore the microdynamics of team processes "below the surface" of these collective-level constructs in order to better understand team behavior and performance (Humphrey & Aime, 2014: 444). For example, network concepts and analysis have been applied to understand team interdependence and communication patterns in the face of team member change and turnover, with studies examining how changes in team membership can differentially impact performance as a function of structural features of the team's network, and the departing individual's place within it (e.g., Argote, Aven, & Kush, 2018; Stuart, 2017). However, this microdynamics approach has yet to be as fully incorporated in the domain of team learning, with extant research tending to conceptualize team learning as a unitary, team-level property (Edmondson, 2002; Vashdi, Bamberger, & Erez, 2013; for a review see Wilson, Goodman, & Cronin, 2007) varying only in amount, and thus implicitly assuming that learning is distributed uniformly and equivalently between all individuals in the team (rather than as a network of differently distributed knowledge [Espinosa & Clark, 2014]). However, each team member may vary in their participation in vicarious learning with other members, as a function of their differing background and position in the team learning network (Singh, Hansen, & Podolny, 2010), and may draw different lessons from another's shared experiences based on the nature of their relationship with the sharer (see Myers, 2018). This potential for differential learning can be better reflected and understood by adopting a network-based model of learning in teams that captures the structure and distribution of vicarious learning relationships among team members.

Additionally, considering team vicarious learning reciprocity opens avenues for better explaining the consequences of teams' learning, and in particular resolving discrepant findings in earlier research regarding team's engagement in learning outside of the team's boundaries (external learning [Ancona & Bresman, 2005]). Teams' engagement in external learning has been shown in prior research to complement their internal learning (the learning with and from other team members discussed above), positively interacting with internal knowledge development in ways that enhance performance (Bresman, 2010), and also to conflict with this internal learning, such that engaging in external learning in addition to internal learning overtaxes team members and harms performance (Wong, 2004). These conflicting results invite a question of whether team members' internal learning may unfold in fundamentally different ways across teams, such that some teams benefit from engaging in external learning and others do not. Yet, because existing research has neglected to explore the underlying patterns of team members' learning from one another, these differences in *how* learning is occurring in a team have been overlooked (in favor of aggregated measures of *how much* learning occurs). Incorporating underlying structural features of a team's network of learning relationships, and in particular reciprocity (as a capacity-building characteristic that could influence team members' ability to absorb additional learning from outside sources), provides a means for disentangling these effects and resolving these conflicting findings.

Finally, given the theoretical promise of reciprocity for broader studies of teams and organizations, this work also contributes by advancing methodological tools for conceptualizing and measuring reciprocity as a characteristic of networks at work. Prior approaches to studying reciprocity in networks within work organizations have typically relied on binary conceptualizations of reciprocity, or have looked only at the relative balance of weighted ties (for recent examples, see Caimo & Lomi, 2014; Kleinbaum, Jordan, & Audia, 2015; Lai, Lui, & Tsang, 2015), making a number of critical simplifications that have limited the field's understanding of reciprocity. In contrast, my approach (drawing upon recent developments in network methods from scholars in the physical sciences [Squartini, Picciolo, Ruzzenenti, & Garlaschelli, 2013]) attends not only to the presence of reciprocal ties but also to their strength. The findings of this study thus contribute not only to literature on individual and team learning by adopting a network-based view of team members' vicarious learning from one another, but also to the organizational literature more generally by advancing reciprocity as a key feature of individuals' networks of relationships at work and providing a robust set of empirical tools for assessing this fundamental network characteristic.

RECIPROCITY IN VICARIOUS LEARNING RELATIONSHIPS AT WORK

Learning vicariously from others' experiences in the workplace has long been considered a valuable process for innovation and performance in organizations (Manz & Sims, 1981). Vicarious learning occurs through individuals being exposed to, and making sense of, others' experience and outcomes (gained through passive means, such as observation, or more active and discursive means, such as storytelling) in their work setting (Myers, 2018). This perspective views others' experience as beneficial for individual learning insofar as making meaning of another's experience helps refine and expand the individual's repertoire of possible responses to future events—focusing less on whether the particular lessons drawn from others' experience are "right" or "wrong" (as this determination depends on how lessons are applied to unknown future challenges) and instead on the benefits that accrue from greater awareness of others' knowledge and experience and a more robust set of responses an individual could apply in the face of future task challenges (see Myers, 2018).

In this way, vicarious learning allows individuals to enhance their own experiential learning processes (i.e., reflecting on and making meaning of their own idiosyncratic set of work experiences) by reflecting on and drawing lessons from others' experiences, gained through inherently interpersonal processes of observation, discussion, and interaction with others in their work environment. Indeed, learning has long been seen as a social phenomenon in organizations that involves action at both the individual and collective level (Argyris & Schön, 1978; Weick, 1979, 1995), leading scholars to consider network-based approaches as a means of understanding organizational learning (i.e., viewing this learning as built on a network of interpersonal connections in organizations [e.g., Glynn et al., 1994; Weick & Roberts, 1993]). In line with this approach, network scholars have examined how the distribution and characteristics of particular relationships (e.g., the strength or embeddedness of a tie [Granovetter, 1973; Uzzi, 1997]) influence learning in organizations (Levin & Cross, 2004). For instance, weak ties were shown in one study to facilitate the search for diverse information in a consulting firm (Hansen, 1999), while Uzzi and Lancaster (2003) found that embedded ties allow for the transfer of more tacit knowledge and experience between bank loan officers and clients.

Whereas the embeddedness of a tie is one feature of a network relationship, another key feature is whether the relationship is reciprocal. Though broadly associated with the strength of a tie (e.g., Granovetter, 1973), the reciprocity of a tie reflects a distinct focus on the tendency of a given pair of individuals to develop mutual connections with each other (rather than just a one-way connection [Newman, 2010]). In terms of vicarious learning, a reciprocal relationship can thus be considered one in which each individual learns from the experiences and knowledge of the other (i.e., in a mutual give-and-take of knowledge [Ipe, 2003]). This can be contrasted with a nonreciprocal (one-way) relationship, where one person shares knowledge and experience with the other but the reverse is not true. Research in communication (e.g., Rogers & Kincaid, 1981) has noted reciprocity to be an integral part of information-sharing, because it helps refine and shape emerging insights from shared knowledge, suggesting that it is key to realizing the learning benefits of a workplace relationship (Adler & Kwon, 2002; Kang, Morris, & Snell, 2007). Indeed, considerations of reciprocity have been tied to organization- and unit-level knowledge-sharing in several prior studies (Dyer & Nobeoka, 2000; Hall, 2001). Studies have found, for instance, that organizational units receiving knowledge from others tended to share their own knowledge with those other units (Lai et al., 2015; Schulz, 2001), while other work has found that perceptions of learning reciprocity are associated with improved chronic illness care in medical clinics (Leykum et al., 2011; Noël, Lanham, Palmer, Leykum, & Parchman, 2013).

Though these studies have generally been conducted at collective levels of analysis, this underlying concern for reciprocity applies to individuals' dyadic vicarious learning at work as well. Sharing knowledge with others can be risky (as others can potentially exploit the information without sharing anything in return [e.g., Empson, 2001]), and so individuals' expectations of reciprocity and trust with another person can drive their motivation to share experiences for the other's learning (e.g., Reinholt, Pedersen, & Foss, 2011), helping to overcome several sources of observed hesitancy among individuals for seeking knowledge from and sharing knowledge with others at work, such as the fear of ceding "ownership" of knowledge (Davenport & Prusak, 1998; Hansen, Mors, & Løvås, 2005; Quigley, Tesluk, Locke, & Bartol, 2007) or the risk of "feeling incompetent or embarrassed" (Hofmann et al., 2009: 1262) from seeking knowledge.

Distinguishing Vicarious Learning Reciprocity

Applied to the context of team learning, reciprocity thus reflects a distinct characteristic of the various member–member dyadic ties that make up a team's vicarious learning network, with unique implications for team processes and outcomes relative to other characteristics of the network. I therefore formally define *team vicarious learning reciprocity* as a compositional construct, consisting of the proportion of reciprocated vicarious learning ties between team members (out of all realized ties in the team network). Though this definition refers to the simple case of unweighted ties (i.e., focusing only on the presence or absence of ties), it is easily adapted to network studies considering tie weight. Specifically, reciprocity of weighted vicarious learning ties can be defined as the proportion of the total tie weight present in both directions between node pairs in the network (out of the total weight of all realized ties in the network).[1]

In this sense, a team's vicarious learning reciprocity is distinct from other characteristics of the team's vicarious learning network, such as its density (Newman, 2010). The density of teams' networks of different work relationships (e.g., task, advice, or hindrance relationships) has been shown to influence team outcomes (e.g., Sparrowe, Liden, Wayne, & Kraimer, 2001; Tröster, Mehra, & van Knippenberg, 2014). Yet, whereas density reflects the proportion of total realized dyadic ties in the network (or total tie weight, in a weighted network) out of all possible ties, reciprocity emphasizes the directionality of these ties, specifically capturing the proportion of bidirectional ties out of all realized ties. In the context of vicarious learning relationships, density can thus be broadly considered as the amount of vicarious learning happening within the team (including vicarious learning that is reciprocated as well as unreciprocated), whereas reciprocity is a feature of the distribution of this overall amount of vicarious learning in the team.

At the same time, reciprocity is also distinct from other forms of the distribution of these ties, such as their centralization. The most basic, and often-used, characterization of network centralization comes from Freeman's (1978) degree centrality, which involves capturing the number of ties a given node is involved in (as a way of assessing which nodes are more "in the thick of" a set of ties), and then comparing the distribution of these centrality values among nodes in the network (i.e., whether most nodes are similar in their degree centrality, relative to the most central node in the network). In a team network, degree centralization thus captures the extent to which ties (or tie weight) are dispersed more evenly across team members versus concentrated among one or more central members, and has been demonstrated as an important characteristic of critical knowledge-sharing structures (Huang & Cummings, 2011), as well as a determining factor in the way teams communicate, develop transactive memory systems, and perform in the face of turnover (Argote et al., 2018). In contrast to this focus on the distribution of tie weight at the team member node level (i.e., the evenness or unevenness of team members' number or strength of ties, relative to other team members), reciprocity focuses on the nature of ties between any given pair of team members (i.e., the extent to which a given pair

[1] I discuss this weighted reciprocity definition (and the novel method used for measuring vicarious learning reciprocity in this study) further in the Methods section.

each have vicarious learning ties with one another). Reciprocity can therefore be distinguished from these other characteristics of a team's network of learning relationships, inviting a consideration of its unique implications for team performance.

CONSEQUENCES OF RECIPROCAL VICARIOUS LEARNING FOR TEAM PERFORMANCE

Organizations have long used teams as a vehicle for channeling individuals' knowledge into performance outcomes, and the effectiveness of this performance is driven by teams discerning and incorporating the relevant experience of each team member (Littlepage, Robison, & Reddington, 1997; Thomas-Hunt, Ogden, & Neale, 2003). Though most perspectives on team learning conceptually recognize this interpersonal sharing of experience, it is typically empirically lost in aggregation at the group level (concluding that the group engages in simply a greater or lesser amount of learning). However, understanding how this learning is distributed across individuals in the team is critical for understanding the performance effects of team learning (e.g., Argote & Ophir, 2002). Importantly, the consequences of how learning is distributed in teams (including the reciprocity of these learning relationships) may vary across different task settings, depending on the extent to which successful team outcomes depend on integrating and coordinating efforts among team members. However, as organizational teams continue to face more complex, knowledge-intensive, and service-oriented work that incorporates the efforts of diverse team members (vs. more disjunctive tasks where a single individual can drive outcomes), the impact of different distributions of these interpersonal learning relationships is likely to be of high importance for understanding team performance.

Direct Performance Effects of Vicarious Learning Reciprocity

Vicarious learning is fundamentally a process of understanding others' experiences, and so directly contributes to an individual's sense of who knows what, or who has done what, in the organization—that is, transactive memory (Brandon & Hollingshead, 2004; Moreland & Myaskovsky, 2000)—and helps individuals develop a shared way of seeing the world—that is, a shared mental model (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). However, though one-way vicarious learning or knowledge-sharing allows the receiver to become more aware of what the sharer knows, the reverse is not true—a sharer is assumed to gain no new awareness about what the receiver may know. Conversely, in a reciprocal vicarious learning relationship, each person develops their understanding and knowledge about the other, affording them a more robust "map" of the expertise in the group, which has been shown to significantly enhance group performance (Hollingshead, Gupta, Yoon, & Brandon, 2012; Moreland & Myaskovsky, 2000).

Moreover, the knowledge or description of experience shared by a team member in a reciprocal vicarious learning relationship is likely to be richer, more complete, and potentially more honest, as the mutual vulnerability and disclosure of this reciprocal relationship yields a stronger sense of trust and closeness, overcoming some of the knowledge-sharing barriers described earlier and encouraging the sharing of more detailed or private information (Uzzi & Lancaster, 2003). In this sense, the learning value of the shared knowledge and experiences in a more reciprocal vicarious learning dyad is likely to be greater (relative to an unreciprocated vicarious learning relationship), both because the knowledge shared is likely to be more nuanced and complete (thereby facilitating more accurate, robust mental maps of others' knowledge) and because the reciprocal sharing of experiences and knowledge in these dyads allows for greater dialogue and comparative analysis of the shared experiences (see Myers, 2018). Indeed, the creation of a more complete shared mental model hinges on individuals' interaction and dialogue, as team members develop their understanding of the others' perspectives through repeated discussion and exchange of information (e.g., Cannon-Bowers, Salas, & Converse, 1993), promoting enhanced future interactions and performance (Mathieu et al., 2000).

Other empirical evidence has supported the performance-enhancing benefits of greater shared mental models and transactive memory as well; for instance, Lim and Klein (2006) observed that combat teams with more shared mental models (regarding their taskwork and teamwork) had higher levels of performance, while Gardner, Gino, and Staats (2012) found that greater familiarity and experience working together (relational resources that serve as key antecedents to transactive memory) facilitate team knowledge integration and team performance. Building on these prior findings, greater reciprocity of vicarious learning should thus have a direct, positive effect on team performance, as it reflects team members' greater understanding of each other's knowledge and mental models, beyond the simple transfer of knowledge and awareness that would occur in a one-way vicarious learning interaction. Therefore, beyond just the amount of vicarious learning occurring in the team, greater reciprocity of this vicarious learning among team members should be positively related with team performance.

Hypothesis 1. Greater reciprocity of vicarious learning among team members is positively associated with team performance.

Vicarious Learning Reciprocity and the Effects of External Learning

Beyond this direct influence of vicarious learning reciprocity on team performance, reciprocity in team members' vicarious learning relationships can also impact performance by altering the performance effects of teams' engagement in external learning. In addition to their internal learning with and from other members within the team, team members often engage in learning beyond the external boundaries of their team (Ancona & Bresman, 2005), through processes such as team member rotation or knowledge transfer through a team member's outside relationships (e.g., Kane, 2010; Uzzi & Lancaster, 2003). Prior work has suggested that both internal and external learning can potentially help a team develop knowledge and perform effectively—by sharing and refining existing ideas or capabilities (internal learning) and discovering new ideas or capabilities (external learning) (Ancona & Caldwell, 1992; Hansen, 1999). However, research has reported conflicting results regarding teams' engagement in this external learning in addition to their ongoing internal learning (Argote & Miron-Spektor, 2011).

Most notably, Wong (2004), in a study of 73 teams from a variety of industries (financial services, health care, technology, and industrial), found support for the hypothesis that greater internal learning promoted greater efficiency (exploitation), while greater external team learning promoted greater innovation (exploration). However, she also found that high external learning reduced the effect of internal learning on teams' efficiency (with no corresponding interaction of internal and external learning on innovation), indicative of a detrimental overall performance effect of engaging in high levels of external learning on top of internal learning (Wong, 2004), potentially because engaging in both forms of learning draws heavily on the team's cognitive, temporal, and attentional resources (detracting from the resources available for performance [Singer & Edmondson, 2008]). In contrast, Bresman (2010) explored a similar question in 62 pharmaceutical teams, hypothesizing that external vicarious learning activities (specifically those in which the team learns about its task from individuals outside the team) increased team performance, particularly for teams engaging in more internal learning activities (consistent with arguments for absorptive capacity [Cohen & Levinthal, 1990]). Results supported both hypotheses, with internal and external team learning complementing one another to enhance performance.

Though there are certainly contextual differences in the setting of the two studies that can partially explain the divergent findings (e.g., pharmaceutical teams being in a more dynamic, fluctuating environment where external and internal learning are less at odds vs. more mature task settings [Bresman, 2013]), the underlying conceptual tension—that team members' internal learning from one another can enable the team to better understand and adopt knowledge from outside of the team (enhancing performance), but can also tie up limited cognitive resources that are then exhausted by engaging in external learning (leaving no resources for performance)—remains. This tension touches on a fundamental challenge of learning, noted by Bunderson and Sutcliffe (2003), in that learning is simultaneously performance-enabling, because it promotes adaptability and ongoing improvement (Argote, Gruenfeld, & Naquin, 2001), and performance-inhibiting, because it consumes resources and diverts attention away from performance (e.g., March, 1991; Singer & Edmondson, 2008). Considering a team's vicarious learning reciprocity may help address these competing tensions (and reconcile conflicting findings), as teams with greater vicarious learning reciprocity should have greater capabilities for integrating knowledge and communicating efficiently among members, allowing them to be both more adaptive and more resource-efficient in their use of internal and external learning.

As noted above, greater reciprocal vicarious learning among team members can generate unique benefits (relative to unreciprocated vicarious learning), such as enhanced trust and greater understanding of others' experiences, that reflect team members' stronger relational capacity for future learning (i.e., the enhanced ability of team members to learn from new information shared by one another in the future, resulting from prior engagement in vicarious learning [Myers, 2018]). In other words, team members who have engaged in more reciprocal vicarious learning with one another possess greater relational resources with which to absorb external knowledge or information brought in by another team member, which should enhance their knowledge integration capability—that is, the capability to create "novel combinations of different strands of knowledge, which have utility for solving organizational problems, from component knowledge sourced from within and beyond the organization" (Zahra, Neubaum, & Hayton, 2019: 10–11). This is consistent with prior findings that stronger relational resources (such as familiarity or shared work experience) are key predictors of teams' knowledge integration capability, particularly under uncertainty (Gardner et al., 2012). Applied to external learning—where knowledge is likely to be more uncertain, unfamiliar, and potentially divergent from the team's existing knowledge (giving rise to the beneficial effects of this learning on innovation [Wong, 2004])—a team's knowledge integration capability is likely to be particularly important for effectively translating and incorporating this knowledge in performance-enhancing ways.

At the same time, greater reciprocity of vicarious learning within the team should aid teams' knowledge communication efficiency, allowing for this knowledge integration to occur in less resource-intensive ways. Teams with greater vicarious learning reciprocity, as noted earlier, should have pairs of team members with greater shared mental models and understanding of each other's perspectives—developed through mutual sharing of experience. This team-level compilation of dyadic understanding of others' perspectives is well-described by Huber and Lewis's (2010) notion of *cross-understanding*. As these authors suggested, cross-understanding can allow team members to learn and perform both more effectively and more efficiently—so that they can devote less time and energy to communicating knowledge:

> Cross-understanding increases the effectiveness of communication by enabling members to choose concepts and words that are maximally understandable and minimally off-putting to other group members. … Without an understanding of one another's mental models, members are apt to make arguments or proposals concerning group processes and products that are technically, politically, or otherwise unacceptable to those whose mental models they do not understand, thus contributing to confusion, conflict or stalemate. (Huber & Lewis, 2010: 10)

Thus, by allowing team members to more quickly and easily communicate to share knowledge with one another, greater vicarious learning reciprocity should enable teams to engage in internal and external learning more efficiently, freeing up resources (i.e., time and attention) to translate this learning into team performance. This is consistent with evidence that teams' shared mental models benefit team performance, in part, through team internal interactional processes such as coordination, cooperation, and communication (Mathieu et al., 2000).

Returning to the conflicting case examples, though few details were made available about the teams in Wong's (2004) study, the description provided by Bresman (2010) of the pharmaceutical teams noted their rich, dense interactions involving significant discussion and feedback (e.g., after "trial and error"), as well as their established working relationships as "core team members" who had been involved with the entire duration of the project—all elements that would seem to support the presence of more reciprocal vicarious learning relationships, potentially explaining the positive results found in his study. Though these assertions are purely *post hoc* interpretations of the sample description, when combined with the arguments above they provide a measure of anecdotal support for the notion that teams' engagement in external learning (in addition to their internal learning) may harm performance, but not in cases where there is more reciprocal vicarious learning among team members. Indeed, by enhancing knowledge integration and communication among team members, and therefore allowing for more effective and efficient learning, teams with greater vicarious learning reciprocity should experience greater performance gains from this external learning.

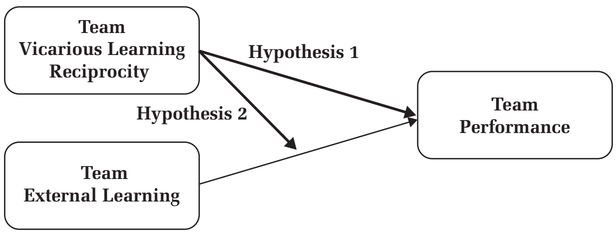
Hypothesis 2. Teams' vicarious learning reciprocity moderates the relationship between their external learning and team performance. Specifically, when vicarious learning reciprocity is higher (lower), greater external learning will be more positively (negatively) associated with team performance.

METHODS

Sample and Procedure

I tested my hypotheses (summarized in Figure 1) in the context of MBA consulting project teams, which consisted of MBA students from a large university in the midwestern United States who traveled and worked full-time in 4–6-person consulting teams over seven weeks on projects for different client organizations around the world. Client organization sponsors provided teams with a current project or challenge faced by the organization and the student teams worked as consultants to gather data, conduct analysis, and offer recommendations for the client organization. As part of a broader data collection effort (used to support multiple studies, including prior research using variables included here as controls [i.e., De Stobbeleir, Ashford, & Zhang, 2019; Zhang, Nahrgang, Ashford, & DeRue, 2020]), students completed multiple surveys over the

FIGURE 1
Conceptual Model



course of their consulting project, during which the data for this study were gathered. These surveys asked students about their own beliefs and behaviors, as well as about their other team members. Client sponsors completed a survey regarding the team's work at the end of the project period.

Sample selection. Singleton and Straits (1993) noted that in order to draw accurate conclusions from a survey study, it is necessary to select a sample appropriate to one's theory and hypotheses. Given my interest in understanding how team members reciprocally (or nonreciprocally) learn from one another in the service of team performance, these consulting project teams provided an ideal context for several reasons. These teams were involved in a realistic, but novel, business challenge that required them to draw on and integrate their background knowledge and diverse prior experiences. The challenges were not limited to a single functional area and team members did not all come from similar backgrounds, providing both a breadth of prior experiences and the impetus for integrating these prior experiences (i.e., the need to integrate across different areas) to promote vicarious learning. In this way, the teams' structure and work were emblematic of the increasingly project-based, dynamic team structures of modern organizations, as well as of the types of knowledge-based services work of the "knowledge economy" (Powell & Snellman, 2004). Indeed, as the world of work becomes increasingly characterized by *ad hoc* teaming, contract work, and shorter job tenures, the features of these MBA project teams (newly formed teams given a specific project and short time duration for integrating knowledge and accomplishing an objective) provide a high degree of relevance and external validity for generalizing this study's findings to other organizational settings.

Additionally, utilizing MBA consulting teams allowed me to test my hypotheses in a context with high response rates, providing an ideal empirical setting for a study of vicarious learning reciprocity, particularly given the whole-network approach (i.e., examining the distribution of learning ties within the entire team) employed within each team. Indeed, while in undirected network studies one individual's response is often taken to indicate the presence or absence of a relationship (even if the other party did not complete the measure), in a directed network (where each direction of the relationship between two people is treated as independent) high response rates are critical (e.g., Burt, 1987; Stork & Richards, 1992). Because the surveys were associated with a major experiential learning program in the school's MBA curriculum, and were seen as a critical part of the program experience, very high response rates were attained in this sample. Specifically related to the vicarious learning measures, only one team provided a response rate lower than 100%; this team was excluded from analysis (as noted below).

Procedure. Prior to beginning the project ("Time 0"), the MBA program office assigned individuals to teams and participants completed a number of pre-program activities, including a broad survey regarding their attitudes toward, and expectations for, the project. Approximately halfway through the project, once teams had experience working together ("Time 1"), participants completed a survey that included items assessing their prior familiarity with each other team member, the extent to which the team had strong norms for learning, and their engagement in feedback-seeking behavior during the team's work. Finally, around the end of the project period ("Time 2"), participants completed another survey that included items assessing their vicarious learning relationship with each other team member, as well as assessing the team's external learning.

A total of 454 first-year MBA students, assigned to 89 different teams, participated in these surveys. As noted above, given the challenges of incomplete data for analyzing reciprocity in network ties (as well as other network parameters [Stork & Richards, 1992]), I excluded one team that did not provide complete responses for the vicarious learning measure from all team members, yielding an initial sample of 88 teams (made up of 450 individuals; on average 27.5 years old and 33% female). At the conclusion of the project, the company project sponsors (i.e., the client for each consulting project) completed a separate survey about the project and their perceptions of the team's work, which included measures of team performance (focusing on both team outcomes and team quality). As not all sponsors completed this survey, team performance ratings were only available for 62 teams (for an effective sponsor response rate of 70%), limiting the final sample size for my analyses ($n = 62$).

Measures

Unless noted, items were assessed on a 5-point Likert-type scale (1–5, with anchors appropriate to the scale). Appendix A lists the scale items for all key measures in the study.

Vicarious learning reciprocity measure. Individuals' vicarious learning was measured via a whole-network, within-team survey (conducted at Time 2) that asked individuals to rate the extent to which they learned from the experiences shared by each other team member. Building from existing measures that assess learning or advice relations (e.g., Cross, Borgatti, & Parker, 2001; Leykum et al., 2011), each individual assessed, for their relationship with each other team member, the extent to which: "[This person] often shares his/her prior experiences, expertise, or knowledge with me to help my learning," and "I am able to draw meaningful lessons from the experiences and information [this person] shares with me." These two items were rescaled from the 1–5 rating provided by respondents to a 0–4 scale to facilitate construction of the network measures described below, and were then averaged to create a measure of an individual's vicarious learning from a given team member ($\alpha = .89$).[2]

This approach generated 1,926 unique assessments of individuals' vicarious learning with other members of their team (among the 88 teams in the initial sample). In constructing the network of vicarious learning relationships in the team, I assessed learning from the perspective of the recipient of shared knowledge or experience (as the sharer may be unaware of whether the other person learned anything from their sharing). A vicarious learning tie (between two team members) therefore consists of each member's assessment of their own learning from the experiences shared by the other. I define the in-degree flows of the tie (the portion coming in to the focal individual) as the individual's reported vicarious learning from the experiences shared by the other, and the out-degree flows as the amount of vicarious learning (reported by the other) stemming from the focal individual's sharing of experience. This is somewhat different from standard approaches to defining in- and out-degree flows in survey-based directed networks, which generally focus on who provided the rating as the determinant of directionality (i.e., self-reported ties are out-degree, and other-reported ties are in-degree). However, I transpose these tie directions in order to generate a more logical depiction of the flow or motion of the network (see Borgatti, Everett, & Johnson, 2018: 202), with directional arrows corresponding to the flow of knowledge and experience between individuals in the network—that is, reflecting the movement of knowledge and experience from sharer to learner (see Online Supplementary Material[3] for further details of this approach and for the calculations of these measures in two sample teams).

Notably, these assessments captured not only the *presence* of a vicarious learning relationship, but more specifically the *extent* of each person's learning from the other's experience (i.e., tie strength or weight, ranging from 0–4). Prior approaches to studying reciprocity in workplace networks have tended to focus solely on the presence or absence of mutual ties by either directly measuring ties as present or absent (i.e., 0 or 1) or dichotomizing weighted tie measures to 0 or 1 based on some minimum tie strength threshold (see, e.g., Caimo & Lomi, 2014; Cross et al., 2001; Kleinbaum et al., 2015). Yet, considering reciprocity only as a binary characteristic masks important considerations of relative tie strength that are critical for understanding complex networks of relationships in organizations. For instance, a learning relationship in which both individuals report learning from each other to a moderate degree (i.e., each reporting 2.5 out of 4) is likely quite different from one in which each individual learns from the other to a very great degree (i.e., each reporting 4 out of 4), but both may be treated as equivalent in a binary approach (depending on the cutoff threshold; see Online Supplementary Material), to the detriment of our understanding of the flow of knowledge within teams.[4]

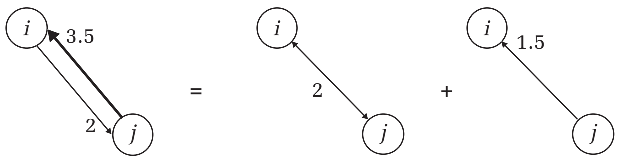
To address this issue, I build on recent developments in network methods (Squartini et al., 2013) to consider vicarious learning reciprocity not as the simple

[2] Two additional items were included in the survey to assess the validity of this measure of individuals' vicarious learning from each other team member. See Appendix B for details.

[3] Online Supplementary Material is available at: https://osf.io/chwpn/?view_only=a4cfdd0ee5414cbcae6b9776bc3e5e80

[4] Other studies have used an approach that examines the balance of in-degree and out-degree flows by taking the absolute value of in-flows minus out-flows (see, for example, Lai et al., 2015). While this approach does not dichotomize reciprocity, it suffers from many of the same limitations, recasting reciprocity as the degree of (im)balance between two nodes and masking the strength of the relationship. To demonstrate this similarity in limitation, consider that in this approach, a relationship consisting of an incoming tie of weight 3 (out of 4) and an outgoing tie of weight 4 results in an equivalent "balance" measure (of 1) as a relationship consisting of an incoming tie weight of 1 and an outgoing tie weight of 2.

FIGURE 2
Decomposition of Tie Weight in an Asymmetric Network Dyad into Fully Reciprocated and Fully Unreciprocated Components



Note: Adapted from Squartini et al. (2013: 2).

presence of bidirectional vicarious learning ties but rather as the strength of the reciprocated tie, such that dyads can have more- or less-reciprocal vicarious learning relationships (rather than simply reciprocal or not). As an example, consider the dyad in Figure 2 (adapted from Squartini et al., 2013), where individual *i* reports learning vicariously from the experience of individual *j* to a relatively large extent (3.5) while individual *j* reports learning vicariously from the experiences shared by *i* to a lesser extent (2). This relationship can be decomposed into a fully reciprocated tie of weight 2 and a fully unreciprocated tie (from *j* to *i*) with a weight of 1.5.

More generally, following Squartini and colleagues (2013), any dyadic relationship $(w_{ij},\ w_{ji})$ can be equivalently decomposed as $\left(w_{ij}^{\leftrightarrow},\ w_{ij}^{\rightarrow}, w_{ij}^{\leftarrow}\right)$, where $w_{ij}^{\leftrightarrow}$ represents the fully reciprocated portion of the tie weight, and $w_{ij}^{\rightarrow}$ and $w_{ij}^{\leftarrow}$ represent the fully unreciprocated portions of the out-degree and in-degree weight (for individual *i*), respectively. This reciprocated weight between *i* and *j* can thus be expressed as $w_{ij}^{\leftrightarrow}=\min[w_{ij},\ w_{ji}]=w_{ji}^{\leftrightarrow}$ and the unreciprocated weight from *i* to *j* as $w_{ij}^{\rightarrow}=w_{ij}-w_{ij}^{\leftrightarrow}$. Notably, if $w_{ij}^{\rightarrow}>0$ then $w_{ij}^{\leftarrow}=0$ (and vice versa), reflecting the fully unreciprocated nature of this portion of tie weight.

Using this decomposition, I calculated the reciprocated and unreciprocated tie weights for the dyadic vicarious learning relationship between an individual and each other member of their team. I then calculated total reciprocated and unreciprocated tie strength for each individual, such that each individual's total reciprocated tie strength ($s_i^{\leftrightarrow}$) is defined as $s_i^{\leftrightarrow}=\sum_{j\neq i}w_{ij}^{\leftrightarrow}$ (and total unreciprocated tie in- and out-strength as $s_i^{\leftarrow}=\sum_{j\neq i}w_{ij}^{\leftarrow}$, and $s_i^{\rightarrow}=\sum_{j\neq i}w_{ij}^{\rightarrow}$, respectively).[5]

Team vicarious learning reciprocity was then calculated using an adaptation of the standard binary approach—which calculates reciprocity as the proportion of the total number of reciprocal ties in the team divided by the total number of ties—to account for weighted ties (again following Squartini et al., 2013) by taking the proportion of the sum of all team members' reciprocated vicarious learning tie weight out of the total (realized) weight of the network:

$$\frac{W^{\leftrightarrow}}{W}=\frac{\sum_{i=1}^{n}s_i^{\leftrightarrow}}{W}=\frac{\sum_{i=1}^{n}\sum_{j\neq i}w_{ij}^{\leftrightarrow}}{\sum_{i=1}^{n}\sum_{j\neq i}w_{ij}}$$

As this formula suggests, this weighted reciprocity measure ranges from 0 to 1 (i.e., from 0 to 100% of tie weight reciprocated within the network). Empirically, the reciprocity values in the final analyzed sample (n = 62) ranged from .65–.98, with an average of .85 (SD = .08; see Online Supplementary Material for more detail on this reciprocity measure and several comparisons to approaches relying on dichotomizing ties to determine reciprocity).

External learning and performance measures. *Team external learning* was measured by surveying all team members (at Time 2) regarding the extent to which the team engaged in information-gathering or learning from a variety of sources outside of the team. Specifically, adapting an approach used in prior research (e.g., Ancona & Caldwell, 1992; Bresman & Zellmer-Bruhn, 2012) to fit the project team context, team members were asked to rate the extent to which their team learned from five different sources: faculty, industry experts, other teams, second-year MBA students, and personal network contacts. Though reliability was somewhat lower than typical thresholds (α = .66), standard measures of intrateam agreement among the 88 teams in the initial sample supported aggregating these ratings to the team level. Specifically, median $r_{\text{wg}(5)}$, as a measure of interrater agreement, was .90 (using a uniform null distribution; 94% of teams had values above .70), and ICC values (calculated for unequal group sizes as described in Bliese [2000: 355]), reflecting both interrater agreement and interrater reliability (LeBreton &

[5] In order to make comparisons at the individual level, these measures would require adjustment to account for differences in the number of ties in each team network. Though not used in the analyses here, comparable scaled measures of individual vicarious learning reciprocity can be created by dividing each strength measure by one less than the total number of team members, which is equivalent to the number of potential dyadic ties for any given individual in the team network. This choice of scaling has the benefit of creating a measure interpretable as the average tie strength (for reciprocated strength, unreciprocated in-strength and unreciprocated out-strength, respectively) for a given individual (see Online Supplementary Material).

Senter, 2007), were: ICC(1) = .23, ICC(2) = .60.[6] Moreover, given that the items of this measure were discrete sources of potential external learning, rather than alternative measures of an identical concept, the reliability coefficient (α) is less relevant to the validity of the measure (as noted by Quigley et al., 2007). Teams' ratings of their external learning ranged from 2.20–4.15, with an average rating of 3.04 (SD = .42) in the final sample (n = 62).

Finally, *team performance* was assessed by the company project sponsors (i.e., the liaison from the client organization for whom the project team was working) using a composite of five items developed by the university MBA program office for assessing the outcomes of the consulting project teams and five items developed by the program office for assessing the quality of the team and their work together. The project sponsor was asked to rate, for example, the team's "productivity (i.e., quantity of work completed)" and "overall team performance" (team outcomes), as well as "the team's ability to work together" and "the overall quality of the [project] team" (team quality). These two sets of items were averaged into a single performance measure in order to capture both outcome- and process-related dimensions of performance.[7] Exploratory factor analysis showed that all 10 items loaded on a single factor, and the reliability of the composite measure was high (α = .94). As noted earlier, ratings were available for only 62 teams, with an average team performance rating of 4.33 (SD = .66) and a range from 1.60–5.00. These values (on a 5-point scale) suggest the presence of an atypical distribution, and in particular potential right-censoring of the team performance ratings (such that the score of 5 acted as a threshold and potentially limited ratings that would have otherwise been higher); thus, tobit regression analysis was used to model the hypothesized effects of vicarious learning reciprocity and external learning on team performance, as described below.

Control measures. To better understand the effects of team vicarious learning reciprocity, I also control for several other features of teams' vicarious learning networks. Specifically, I control for *team vicarious learning density* in order to isolate the effects of the distribution of vicarious learning (i.e., as more- or less-reciprocated) above-and-beyond the effects of the overall amount of vicarious learning in the team. I calculate vicarious learning density as the total weight of the vicarious learning ties present in each team's network, divided by the maximum potential weight of vicarious learning ties in the network:

$$\frac{W}{W^{max}} = \frac{\sum_{i=1}^{n}\sum_{j\neq i} w_{ij}}{n(n-1)\times w^{*}}$$

where n is the number of team members and w^{*} represents the maximum network tie weight.

I also control for *team vicarious learning centralization* in order to understand the effects of reciprocity alongside how centralized vicarious learning ties are in the network (as another form of tie distribution). Drawing from Freeman's (1978) classic characterization of centrality as reflecting individuals who are "in the thick of things," I focus here on individuals' total degree centrality in the team vicarious learning network to capture differences across teams in the extent to which vicarious learning interactions were more concentrated among certain team members. Following Freeman's definition, as well as more recent guidance on calculating centralization within asymmetric, weighted networks (see Wei, Pfeffer, Reminga, & Carley, 2011), I calculate team vicarious learning total degree centralization by first calculating the total degree centrality of each individual in the team (simultaneously accounting for both in-degree and out-degree tie weights) as $C_i^{total} = (\sum_{j\neq i} w_{ij} + \sum_{j\neq i} w_{ji})$. Team total degree centralization can then be defined as the sum of differences between the team's most central member and each other member, divided by the maximum potential value of this difference:

$$\frac{\sum_{i=1}^{n}\left(C^{*\ total} - C_i^{total}\right)}{Max\sum_{i=1}^{n}\left(C^{*\ total} - C_i^{total}\right)}$$

where $C^{*\ total}$ represents the node with the highest total degree centrality among nodes in the network (see Online Supplementary Material for more detail on the calculation of this measure).

[6] Simulation studies have shown that the use of shorter Likert-type scales and small group sizes can generate substantially underestimated values for ICC(1) and ICC(2), respectively (Beal & Dawson, 2007; Bliese, 1998). As the data aggregated in this study come from 5-point Likert-type scales provided by individuals in 4–6-person groups (meeting both criteria above), reported ICC values should be interpreted as potentially underestimated.

[7] Eight teams received ratings from multiple sponsors (i.e., 2–3 liaisons from the same client organization) for at least some of the items included in this measure, and so scores for each item were averaged across available ratings before constructing the team performance measure.

In addition to these network constructs, I control for team members' relevant learning attitudes and behaviors during the project. Specifically, I control for *team learning norms,* which were assessed (at Time 1) using a 5-item measure adapted from existing studies (Bunderson & Sutcliffe, 2003; Quigley et al., 2007). Each team member assessed the extent to which they felt the team had norms or expectations that "team members should seek out opportunities for the team to learn," that "team members should share information when it might help others," that "team members should go out of their way to help others with a problem or question," that "team members should be willing to take risks on new ideas to find out what works," and that "team members should see learning and developing skills during [the program] as an important goal" ($\alpha = .83$ among the 450 individuals in the initial sample of 88 teams). As these learning norms reflected a shared group construct (Klein & Kozlowski, 2000) among team members, individuals' ratings were tested for intragroup agreement among the 88 teams (median $r_{wg(5)} = .91$, using a uniform null distribution, with 93% of teams above .70; ICC(1) = .09, ICC(2) = .33)[8] and aggregated into a single, team-level rating of shared learning norms. Likewise, I control for individuals' engagement in *feedback seeking behavior*, measured (at Time 1) using three items adapted from Ashford (1986)—assessing the extent to which individuals "directly asked your teammates for feedback about the quality of your work," "directly asked your teammates for feedback on your teamwork skills," and "directly asked your teammates for feedback on your project management skills" ($\alpha = .87$ among the 450 individuals in the initial sample of 88 teams)—and averaged individual's scores to create a team-level measure.

In order to further reduce the probability that confounding variables may influence my results, I control for team size, familiarity, and demographic characteristics (specifically age and gender) in my analyses. Though many of the study measures are scaled to account for team size, the *number of team members* (i.e., the size of the network) may still have unaccounted-for effects on the propensity for strong ties to form, as well as on other unscaled measures, and is thus included as a control variable. *Familiarity* is included as a control to account for heterogeneity in teams' prior experience interacting or working together. At Time 1, all team members were asked to rate the extent to which they had known each of their other team members prior to the project (using a single-item measure). These ratings were averaged at the individual level (i.e., for all team member ratings of the focal individual) to create an individual-level measure of familiarity, and then aggregated to the team level by averaging the familiarity ratings of all members of the team. Finally, *age* and *gender* (obtained from archival program measures) were included as demographic controls, calculated as the mean age of team members and the proportion of female team members (i.e., the team average of a dummy variable where 0 = male and 1 = female), as these may influence individuals' decision to engage in learning and knowledge-sharing with others in the team (e.g., Singh et al., 2010), and can affect the overall pattern of interpersonal relationships that develop within a team (e.g., Lau & Murnighan, 1998; Pelled, 1996).[9]

ANALYSIS AND RESULTS

Means, standard deviations, and correlations of study measures in the final sample of 62 teams are presented in Table 1. Given the distribution of the team performance measure noted above (specifically, the potential censoring of these ratings on the high end), I constructed tobit regression models using maximum likelihood estimation with robust standard errors in Mplus Version 7 (Muthén & Muthén, 2012) to test my hypotheses.[10]

Specifically, to test Hypotheses 1 and 2, regarding the direct and interactive performance effects of teams' vicarious learning reciprocity, I first constructed a model including the control measures described above predicting team performance ratings (Table 2, Model 1). I then entered the measure of team vicarious learning reciprocity (Table 2, Model 2), which was a significant, positive predictor of

[8] Though this value for ICC(2) was lower than that typically reported for adequate agreement, the high median r_{wg}, combined with the potential underestimation of ICC values described earlier, suggest that aggregation of this construct is justifiable. Moreover, as described below, results from a robustness check reveal that the hypothesized effects hold while excluding all of the covariates, such that including or excluding this measure does not alter my conclusions.

[9] Age data could not be identified or matched for three individuals (all on different teams) in the sample. Given the low frequency and distribution (across teams) of this missing data, team means for age were constructed for teams disregarding the missing data on these individuals.

[10] The Online Supplementary Material includes results from simpler linear regression models, which demonstrated support for both hypothesized effects.

TABLE 1
Means, Standard Deviations, and Correlations

Variable	Mean	*SD*	1	2	3	4	5	6	7	8	9	10
1. Team Size	5.03	.92										
2. Female Team Members (%)	.31	.25	.15									
3. Average Team Member Age	27.61	1.21	−.18	−.28*								
4. Average Team Member Familiarity	1.94	.43	−.01	.18	.08							
5. Feedback Seeking Behavior	2.34	.58	.01	−.04	.07	.14						
6. Team Learning Norms	3.87	.35	−.13	−.17	.02	−.05	.12					
7. Team Vicarious Learning Density	.74	.09	−.30*	−.03	.17	−.11	−.14	.43***				
8. Team Vicarious Learning Centralization	.14	.07	.01	.10	−.17	.20	.19	−.19	−.47***			
9. Team Vicarious Learning Reciprocity	.85	.08	−.31*	.03	.08	−.25*	−.27*	.26*	.68***	−.38**		
10. Team External Learning	3.04	.42	.10	.12	.01	−.04	.22†	−.06	−.08	.00	−.30*	
11. Team Performance	4.33	.66	−.15	.13	.24†	.07	−.02	.14	.24†	−.16	.39**	−.12

Note: $n = 62$ teams.
† $p \leq .10$
* $p \leq .05$
** $p \leq .01$
*** $p \leq .001$

team performance (b = 4.60, p = .004), providing support for Hypothesis 1. I next entered the measure of team external learning (Table 2, Model 3) which was a nonsignificant predictor of team performance (b = −.01, p = .96), followed by the interaction of team vicarious learning reciprocity and team external learning (Table 2, Model 4). These results revealed a significant interaction between vicarious learning reciprocity and external learning in predicting team performance (b = 6.02, p < .001), in support of Hypothesis 2.

To explore this significant interaction further, I plotted (see Figure 3) and tested the slopes of the relationship between external learning and team performance at several different levels of team vicarious learning reciprocity. Results revealed that greater team external learning had a significant, negative association with team performance when team vicarious learning reciprocity was 1.5 standard deviations below the mean (corresponding to 73.41% of vicarious learning tie weight reciprocated; β = −.62, p = .01), and a marginally significant negative association when vicarious learning reciprocity was 1 standard deviation below the mean (corresponding to 77.24% reciprocity; β = −.39, p = .06). However, when team vicarious learning reciprocity was 1.5 standard deviations above the mean (corresponding to 96.39% reciprocity), the association between external learning and team performance was significant and positive (β = .76, p = .03), and it was marginally significant and positive when team vicarious learning was 1 standard deviation above the mean (corresponding to 92.56% reciprocity; β = .53, p = .06). The association between external learning and team performance was nonsignificant at the mean value of team vicarious learning reciprocity (corresponding to 84.90% reciprocity; β = .07, p = .74). Taken together, these results support the hypothesized directional predictions in Hypotheses 2, such that when vicarious learning reciprocity was lower, greater external learning was more negatively associated with team performance, but when reciprocity was higher, the association between greater external learning and team performance was more positive.

To test the robustness of these results, I constructed models excluding all of the control variables. In support of both hypotheses, these models revealed that vicarious learning reciprocity was a significant predictor of team performance (b = 3.75, p = .003; Table 2, Model 5), and further revealed a significant interaction between vicarious learning reciprocity and external learning (b = 6.67, p = .001; Table 2, Model 6) on team performance (see Online Supplementary Material for additional robustness tests).

DISCUSSION

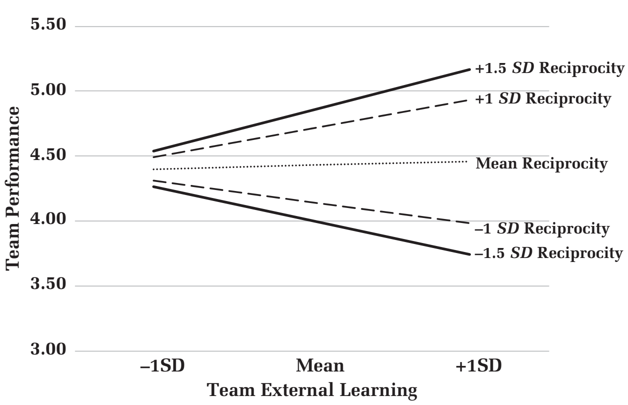
Drawing from a network-based view of learning in teams, this study examined the performance impact of reciprocity in vicarious learning relationships among team members. In contrast to prior views of vicarious learning as uniform and unidirectional within teams, a reciprocity-focused perspective reveals key differences in the underlying distribution of vicarious learning relationships among team members that can influence how teams learn and perform. Specifically, results revealed that greater

TABLE 2
Tobit Regression Analyses Predicting Team Performance

	Primary Analyses				Supplemental Robustness Analyses	
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−1.36 (2.21)	−4.23 (2.26)†	−4.18 (2.35)†	12.25 (5.15)*	1.20 (1.07)	19.01 (5.83)***
Team Size	−.10 (.11)	−.04 (.10)	−.04 (.10)	−.03 (.10)		
Female Team Members (%)	.62 (.35)†	.49 (.29)†	.49 (.30)	.17 (.27)		
Avg. Team Member Age	.15 (.06)**	.15 (.06)**	.15 (.06)**	.14 (.05)**		
Avg. Team Member Familiarity	.16 (.20)	.30 (.20)	.30 (.20)	.27 (.18)		
Feedback Seeking Behavior	.05 (.16)	.13 (.14)	.13 (.15)	.13 (.14)		
Team Learning Norms	.24 (.29)	.24 (.27)	.24 (.27)	.20 (.26)		
Team VL Density	.85 (1.16)	−1.57 (1.47)	−1.56 (1.47)	−1.33 (1.23)		
Team VL Centralization	−1.25 (1.63)	−1.00 (1.60)	−1.01 (1.62)	−.90 (1.57)		
Team VL Reciprocity		**4.60 (1.59)****	**4.57 (1.61)****	−14.61 (5.64)**	**3.75 (1.24)****	−17.47 (6.80)**
Team External Learning			−.01 (.23)	−5.04 (1.39)***		−5.58 (1.74)***
Team VL Reciprocity × Team External Learning				**6.02 (1.71)*****		**6.67 (2.05)*****
R^2	.18*	.28**	.28**	.33**	.15†	.24**

Notes: Reported values are unstandardized regression coefficients, with standard errors in parentheses. Values in bold are hypothesized effects. VL = Vicarious Learning. $n = 62$ teams.
†$p \leq .10$
*$p \leq .05$
**$p \leq .01$
***$p \leq .001$

FIGURE 3
Moderating Effects of Team Vicarious Learning Reciprocity on the Relationship Between Team External Learning and Team Performance



Notes: Plotted values are based on tobit regression model coefficients, setting all covariates to their mean values in the final analyzed sample ($n = 62$). Solid lines represent slopes that are significant at $p \leq .05$; dashed lines represent slopes that are significant at $p \leq .10$; dotted lines represent nonsignificant slopes.

reciprocity of vicarious learning within a team was positively associated with team performance, both directly and through its moderation of the performance effects of external learning. These effects were essentially reversed depending on the team's vicarious learning reciprocity, such that greater external learning benefitted the performance of higher-reciprocity teams, but inhibited that of lower-reciprocity teams.

Contributions

Introducing a network-based view of the underlying microdynamics of team member learning, and specifically the concept of vicarious learning reciprocity, advances the literature on team learning in several important ways. Reciprocity represents a fundamental structural feature of interpersonal learning relationships (and their aggregation to team-, unit-, or organization-level learning), and demonstrating performance consequences of this reciprocity provides empirical evidence of the importance of adopting a dyadic network approach for understanding team learning. Further, by bringing an intrateam network approach (in contrast to the interunit or interorganizational focus of much knowledge transfer research [Hansen, 1999]), the findings of this study help to clarify major theories of group learning, which acknowledge "sharing knowledge" as key components, but provide little detail about the nature of this sharing process (e.g., Wilson et al., 2007). As noted earlier, much research has aggregated this sharing behavior to a property of the team as a whole, implicitly assuming that sharing occurs uniformly and smoothly across all team members. By considering individuals' reciprocity in their vicarious learning with other team members, the model presented here provides a dyadic-level explanatory mechanism for differences in teams' ability to learn from their members' unique experiences and knowledge.

At the same time, focusing on reciprocity of vicarious learning challenges a long-standing (albeit often implicit) assumption in prior literature that learning occurs only in one direction between individuals (e.g., novices learning from experts). In the realm of knowledge-sharing (and related research on advice seeking, as well as knowledge transfer between units or organizations [e.g., Argote & Ingram, 2000; Hofmann et al., 2009; Quigley et al., 2007; Uzzi & Lancaster, 2003]), existing studies have tended to focus on the antecedents or impact of either knowledge-sharing *or* knowledge-seeking, casting the learning relationship as markedly one-way (i.e., only moving from sharer to receiver). Indeed, these studies have typically focused on a single actor in the relationship, assessing their perceptions of the other and using these perceptions to predict knowledge transfer outcomes (e.g., Levin & Cross, 2004; Siemsen, Roth, Balasubramanian, & Anand, 2009).[11] The model presented here simultaneously attends to vicarious learning in both directions within a dyad, while also placing more emphasis on the overarching process of *learning* (vs. just seeking or sharing knowledge) in these interactions. Seeking or sharing knowledge is a necessary, but not sufficient, component of the learning process, as sought knowledge may not be shared, and shared knowledge may not actually be absorbed or interpreted. By placing conceptual and empirical emphasis on individuals' perceived learning from others' experience (i.e., by theorizing and measuring how much an individual reports learning from the experiences of others, rather than just how much is shared), this study more directly addresses the process of learning, rather than inferring learning from the presence of constituent components (e.g., seeking or sharing knowledge). A vicarious learning lens may thus provide a means for integrating prior research on knowledge sharing and knowledge seeking into a more unified perspective of interpersonal learning at work, while also providing a mechanism of aggregation to the collective level through the distribution of vicarious learning dyads within the broader group, team, or organization.

The team performance outcomes associated with vicarious learning reciprocity (especially via its moderation of the effects of external learning) also carry important implications for the study and practice of external learning in teams. Channeling a fundamental paradox of organizations—the need to engage in both exploratory and exploitative learning (March, 1991) in an "ambidextrous" way (O'Reilly & Tushman, 2013)—conflicting evidence on the relative benefits and consequences of engaging in external learning, in addition to ongoing engagement in internal learning, presents a challenge to studies of team learning. Though typically applied at the organizational level, concerns for ambidexterity and balancing exploration and exploitation nonetheless result from the efforts of individuals to learn from one another within a situated "space" in the organization (Miller, Zhao, & Calantone, 2006), such as a team. Balancing this distal and local learning thus requires the purposeful management of resources and integration capabilities to overcome the intrinsic inefficiencies of engaging in both types of learning (O'Reilly & Tushman, 2013), and prior research has observed different results of these balancing efforts (Bresman, 2010; Wong, 2004). Greater reciprocity of vicarious learning between team members presents an integration and resource-allocation mechanism that can help to explain when teams are more- or less-effective in their attempts at ambidexterity, addressing calls for greater attention to the microprocesses underlying organizational ambidexterity (Edmondson et al., 2007). The results of this study suggest that greater vicarious learning reciprocity may be allowing teams to more efficiently and effectively integrate external learning, alongside their internal learning, in ways that enhance performance.

Beyond these contributions to the study of learning in organizational settings, this work contributes more generally to research on the microdynamics of team processes. Operating from a view that teams (and particularly the cross-functional teams common to organizations in the knowledge economy) are inherently relational, interdependent, and interpersonally organized entities (Humphrey & Aime, 2014)

[11] In one notable exception that did examine the role of sharer and recipient together, Quigley and colleagues (2007) demonstrated different motivational antecedents for sharing knowledge (based on norms and incentives) and recipients utilizing the shared knowledge (based on self-efficacy, trust, and self-set goals) in a dyadic knowledge-sharing experiment. However, their study nonetheless treated sharing and receiving knowledge as independent processes—examining what motivates individuals to share knowledge, and the separate motivators for using knowledge—with less attention paid to the nature of the sharing–learning interaction.

this work has begun to make use of compilation-based measurement approaches (i.e., considering the underlying distribution of team constructs, rather than only their average [see Sinha, Janardhanan, Greer, Conlon, & Edwards, 2016]), as well as adopting network perspectives to capture the underlying relationships between individuals in the team. Though these network perspectives have generally focused on density and centralization as relevant features of a team network (e.g., Argote et al., 2018; Stuart, 2017), reciprocity seems to be a particularly relevant characteristic of team members' relationships at work, as many work contexts in modern organizations offer opportunities for significant, bidirectional engagement with peers on the team. Thus, the conceptualization and method for assessing reciprocity advanced here offers a contribution to organizational studies more broadly.

Indeed, from a methodological perspective, existing research on reciprocity in workplace networks (e.g., Caimo & Lomi, 2014; Cross et al., 2001; Kleinbaum et al., 2015; Lai et al., 2015) has tended to use methods that simplify the concept of reciprocity by measuring only the presence or absence of mutual ties (i.e., creating a binary network), by dichotomizing weighted tie measures to a binary network based on some minimum tie strength threshold, or by subtracting the two component tie weights from one another (i.e., creating a measure of the absolute balance or "perfect reciprocation" of each tie). These simplifications mask critical characteristics of these dyadic relationships. Though this problem is not restricted to organizational studies (as binary approaches to reciprocity have predominated most network studies [Squartini et al., 2013]), by adopting conceptual approaches from other disciplines and demonstrating their utility in organizational research this study offers a path forward for scholars of organizations interested in reciprocal processes. The tie-decomposition approach used in this study allows for more robust investigations of reciprocity in weighted networks, while also being fully "backward compatible" with unweighted networks (as the decomposed tie weights, $w_{ij}^{\leftrightarrow}$, $w_{ij}^{\rightarrow}$, $w_{ij}^{\leftarrow}$, reduce to a dichotomous measure for unweighted ties). Considering reciprocal tie strength opens new avenues for research in organizations; for instance, exploring what factors might strengthen or weaken a preexisting reciprocal tie, or what might drive the unreciprocated in-strength and out-strength components of dyadic ties.

From a practical standpoint, the conceptual model and empirical findings presented here carry important implications for how learning is enacted in organizations. By acknowledging reciprocity as an impactful feature of interpersonal learning relationships in organizations, managers might redirect efforts for promoting these relationships, reframing mentoring programs (for example) to emphasize bidirectional learning between mentors and protégés. Likewise, organizational teams would likely benefit from investments in greater opportunities for vicarious learning where these reciprocal learning interactions might be more likely (e.g., face-to-face meetings), particularly when teams need to engage in external learning for a project's success.

Limitations and Future Directions

This study used a sample of MBA student consulting teams, which presented several conceptual and methodological advantages, not least of which was providing the high response rates necessary for studying reciprocity. Further, these teams were engaged in full-time work with their team for an organizational client, similar to consulting teams working in many organizational contexts, providing a relatively high degree of external validity to the sample. However, despite these noted contributions and strengths, the sample used in this study has several limitations that warrant attention and could inspire future research in this domain.

For instance, teams in this sample had generally very high team performance ratings and high levels of vicarious learning reciprocity (as well as high levels of vicarious learning density and low levels of vicarious learning centralization). Given the context of MBA teams engaged in consulting work as part of their degree program, it is possible that the high sponsor-rated performance scores are due, at least in part, to a general inflation of ratings, while the high levels of vicarious learning reciprocity and density may be due to the educational nature of the team assignment (as participants knew that the dual goals of the project were their learning and the delivery of a high-quality consulting project to the client). Future research is needed in other contexts where these values may be lower, in order to explore these concepts across a wider range of vicarious learning reciprocity and performance.

Similarly, team members had relatively little experience working with one another (evident in the low average familiarity scores), likely because individuals were assigned by the MBA program based on a desire to create mixed teams based on students' declared degree concentrations. Though this sort of *ad hoc*, dynamic team membership is becoming increasingly common in organizations, in settings where teams are established for long durations and multiple projects there is important potential for exploring how reciprocity in vicarious learning might be influenced by team members' shared prior experiences. For instance, it is possible that a large volume of shared prior experiences might encourage greater vicarious learning, as the shared experiences provide a common "core" that individuals can reference when sharing their unique experiences for others' learning. On the other hand, greater shared experience working together could also reduce the need for vicarious learning (as individuals would have more shared than unique experiences). Exploring these learning processes in teams with greater tenure and shared experience might thus help better explain the boundary conditions and temporality (i.e., how learning relationships evolve or change over time) of reciprocal vicarious learning.

One additional feature of these teams that deserves future research attention lies in the fact that there were no designated leaders or formal power differences among team members. While differences in informal influence no doubt emerged as the teams progressed through the project, an absence of formal hierarchy and assigned positions of power allowed for a relatively unfettered view of vicarious learning in the team. Indeed, power and status differences in teams alter individuals' performance, participation, and communication (e.g., Katz & Benjamin, 1960; Wittenbaum, 2000), and can affect the way in which knowledge and expertise are shared in the group (Singh et al., 2010; Thomas-Hunt et al., 2003). However, these power dynamics are inherent to the work of many organizational teams, and future research is needed to understand how vicarious learning might change when reciprocity intersects formal power relationships. Prior research has shown that formal hierarchical relationships between organizational units can provide a conduit for greater advice seeking and advice sharing (Caimo & Lomi, 2014; Cross & Sproull, 2004), and it seems likely that the knowledge and experiences individuals share with others in a similar position of power (e.g., peers) versus in a higher position of power (e.g., a supervisor) might differ, such that individuals may be less likely to engage in reciprocal vicarious learning with those in high power. Research exploring the difference in vicarious learning content, differences in the tendency for reciprocation within different power dynamics, or organizational interventions that encourage greater vicarious learning across hierarchical levels (i.e., executives hosting open "office hours" to learn from subordinates) would provide a meaningful extension to the findings presented here.

In addition to these limitations of the study setting—and the corresponding need for future research across a wider range of team environments—this research represents merely an initial exploration of the role of vicarious learning reciprocity in team learning and performance. Additional research is certainly needed to explore antecedents of reciprocity in individuals' vicarious learning relationships, to more directly measure mediating processes that explain the performance effects of this reciprocity, and to consider other consequences (e.g., team member attitudes, declarative knowledge, or performance perceptions) of vicarious learning reciprocity in organizations. Finally, the research questions here focused solely on dyadic reciprocity, but reciprocity may take multiple forms; for instance, reflecting more generalized reciprocity within the team (e.g., where team members may not immediately reciprocate vicarious learning to a sharer, but rather "pay it forward" to other team members [e.g., Baker & Bulkley, 2014]). Examining these more complex forms of reciprocity would be of value for better understanding workplace learning, particularly in larger networks (i.e., beyond small team networks).

CONCLUSION

This study examined the performance benefits of reciprocity in individuals' vicarious learning relationships with other members of their work team. Advancing prior approaches that aggregate team learning as a uniform, group-level property or consider vicarious learning as a unidirectional relationship, this study theorized and tested vicarious learning reciprocity as an important underlying characteristic of team learning and performance, contributing to a more nuanced, interpersonal network view of learning in teams and organizations.

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APPENDIX A

SCALE ITEMS FOR KEY MEASURES

Vicarious Learning

Please assess the degree to which you agree with the following statements about your learning relationship with [Name*] (Strongly Disagree–Strongly Agree)

- [Name*] often shares his/her prior experiences, expertise, or knowledge with me to help my learning.
- I am able to draw meaningful lessons from the experiences and information [Name*] shares with me.

**Repeated for each other team member*

External Team Learning

To what extent did your team engage in learning with (i.e., gathered information from, or asked questions of) the following sources (Never–Very Often)

- Faculty
- Industry Experts
- Other [Program] Teams
- MBA 2s [Second-Year MBA Students]
- Personal Network Contacts

Team Performance (Completed by Client Sponsor)

Team Output Items. Please rate the performance of the [program] team on the following dimensions (Poor–Excellent):

- Productivity (i.e., quantity of work completed)
- Completing work on time
- Providing innovative products or services
- Responding quickly to problems or opportunities
- Overall team performance

Team Quality Items. Please rate each of the following aspects of your [program] team (Poor–Excellent):

- The team's professionalism
- The team's communication with you
- The overall quality of the [program] team
- The team's ability to establish a high-quality relationship with you or other key people in the company
- The team's ability to work together

APPENDIX B

DYADIC VICARIOUS LEARNING RECIPROCITY MEASURE VALIDATION

Two items were used to assess an individual team member's vicarious learning from each other team member, as described in Appendix A. At the same time, two additional items were included in the survey to assess the validity of this measure of individuals' vicarious learning from each other team member. Specifically, individuals were also asked to report their own sharing of knowledge with each other team member ("I often share my own prior knowledge and experience with [Name] to help his/her learning") as well as to assess their overall perception of collaborative learning and knowledge-sharing between themselves and each other team member ("[Name] and I are able to collaboratively build our knowledge and understanding by sharing our own experiences with one another").

At the tie level ($n = 1{,}926$ reported ties among the 450 individuals, in 88 teams, in the initial sample), an individual i's reported vicarious learning (i.e., the extent to which individual i reports learning vicariously from experiences shared by team member j; the average of the two vicarious learning items in Appendix A) was significantly correlated ($r = .19$, $p < .001$) with the corresponding team member j's assessment of their own sharing of knowledge with individual i (i.e., the extent to which j reported sharing knowledge with i on the first additional item, described above, when completing j's own survey). Moreover, the response individual i provided to the second additional item described above (regarding their perception of collaboratively sharing knowledge and experience) for each tie with another team member j was significantly correlated ($r = .61$, $p < .001$) with the reciprocated vicarious learning tie weight between i and j ($w_{ij}^{\leftrightarrow}$, computed as described in the text).

These correlations provide support for the measurement approach taken in this study. Indeed, individuals' perceptions of learning from another's experiences were significantly related to that other's report of sharing knowledge with the individual (and the lower value of this correlation is consistent with broader concerns regarding self-report knowledge-sharing measures, as described in the text), and individuals' general perceptions of a collaborative learning and knowledge-sharing relationship showed a significant relationship to the more specific, multi-source measurement of reciprocal vicarious learning used in this study.