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VARIANCE IN GROUP ABILITY TO TRANSFORM RESOURCES INTO PERFORMANCE, AND THE ROLE OF COORDINATED ATTENTION

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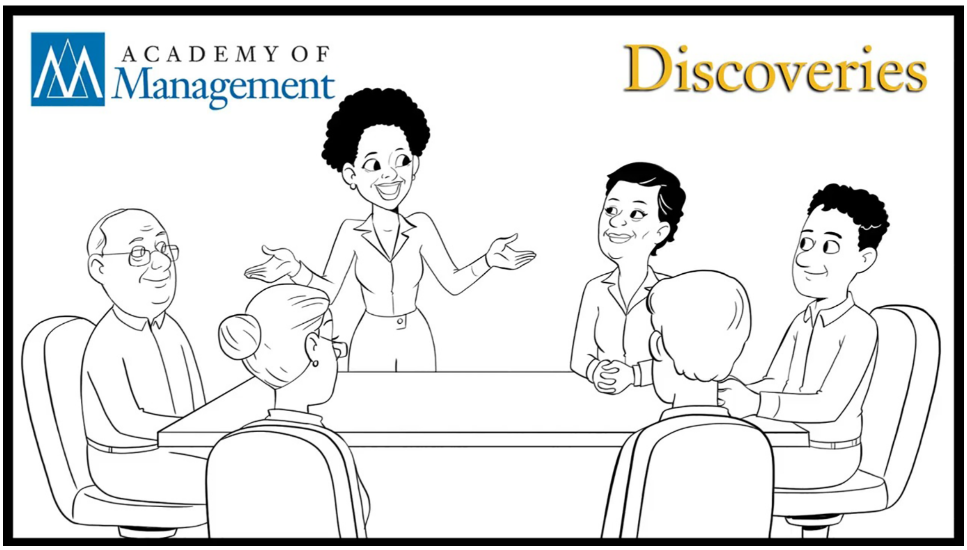


Theory on group performance has long suggested that groups exhibit variance in their ability to transform resources into performance, but empirical approaches have typically examined the average effects of resources, thereby masking such group-specific variance. In this paper, we take advantage of a large panel data set within the context of retail-banking sales groups, along with an econometric method used and advocated for in strategy research (a random coefficient model), to explore whether groups exhibit variance in the extent to which they transform resources into performance. We discover that groups do differ in the returns they achieve to resources, and they do so systematically—returns to one resource correlate with returns to another. These results indicate a latent, general ability to transform resources, one that we find is associated with a group's coordinated attention (manifest in "bursty" email communication patterns). We suggest that the discovered general ability reflects collective intelligence, and we discuss implications of our findings for research on collective intelligence, as well as the implications of our approach for surfacing new phenomena currently masked by the dominant focus on average effects.

INTRODUCTION

Research on groups and teams has long recognized the importance of not only having resources[1] but using them well to perform effectively (e.g., Hackman & Katz, 2010; Steiner, 1972). For example, knowledge is one important resource that groups

[1] We use the term resource broadly here, to indicate some source from which output is generated. Following discussions of resources by Porter (1980) and Barney (1991), we include in our definition labor and various sources of capital, including human capital (e.g., knowledge, experience, skills), social or relational capital (e.g., experience working together, relationship strength), physical capital (e.g., raw materials, technology, location, market position), and financial capital (e.g., research and development).

have, but groups vary in how well they use it; extant research has demonstrated that how well group members share (Bunderson & Sutcliffe, 2002), transfer (Kane, 2010), pool (Larson, Christensen, Abbott, & Franz, 1996; Stasser, Stewart, & Wittenbaum, 2005; Stasser & Titus, 1985), and integrate and elaborate on the knowledge they have (Gardner, Gino, & Staats, 2012; Tiwana & McLean, 2005; van Knippenberg, De Dreu, & Homan, 2004; van Knippenberg & Schippers, 2007) affects the group's performance. Embedded in this work on group processes is the assumption that groups with the same resources vary in the extent to which they transform those resources into performance. As such, the same resources should have different effects across groups.

Author's Voice:
What motivated you to undertake this research?

Despite the theoretical recognition that groups vary in the extent to which they bring resources to bear on a task, common approaches to studying group resource use have often masked this variance empirically. Rather than capture this between-group variance in resource use, research on group performance has often examined the average effect—for all groups—of both the resources themselves and the processes by which those resources might be applied (e.g., Cummings & Pletcher, 2011; Faraj & Sproull, 2000; Gardner et al., 2012). For example, Gardner, Gino, and Staats (2012) estimated the average effects of knowledge resources on performance. While this approach is informative, it assumes that knowledge resources have the same effects for all groups; the effects of knowledge resources on performance do not hinge on either the group's communication behavior (which Gardner et al. [2012] called a knowledge integration capability) or any other process or group-specific ability to transform that knowledge into output. We argue that masking this between-group variation limits our ability to ultimately explain differences in group performance. To extend those findings, we propose that researchers should look at how the effects of knowledge resources vary from team to team such that, given the same knowledge, certain teams benefit more than others.

To this end, contingency models offer one approach to accounting for between-group variance in the effect of a given resource on performance; yet here, too, our ultimate ability to explain variance in group performance might be limited. Continuing with the example of knowledge resources, research has demonstrated how the effect of knowledge on performance is amplified by factors that stimulate better use of that knowledge, with these factors ranging from perspective-taking (Hoever, van Knippenberg, van Ginkel, & Barkema, 2012) to collaborative planning (Woolley, Gerbasi, Chabris, Kosslyn, & Hackman, 2008). These contingency approaches go beyond merely examining an average effect of resources on performance; they create a more nuanced understanding of how groups differ in their ability to transform resources into output. However, these contingency approaches rely on moderating variables (and no other potential sources of variation) to explain group differences in the use of a single resource. We suggest that such approaches also overlook the possibility of a more general, group-specific ability to use a range of resources, such as that suggested by theories of collective intelligence (Woolley, Aggarwal, & Malone, 2015b). If such ability exists, accounting for it should enhance our explanations of group performance. In the current paper, we explore this possibility.

To examine whether groups exhibit a group-specific ability to use a variety of resources, we import to groups research an econometric method used and advocated for in strategy research (Alcácer, Chung, Hawk, & Pacheco-de-Almeida, 2018; Chung & Alcácer, 2002; Knott, 2008; Pacheco-de-Almeida, Hawk, & Yeung, 2015; Swamy & Tavlas, 1995): a random coefficient model (RCM; also referred to as a mixed-effects model with varying slopes, and as a generalized hierarchical linear model). Using a large panel data set within the context of retail-banking sales groups, and simultaneously focusing on two types of resources, results reveal that groups do exhibit variance in the extent to which they transform those resources into output. Moreover, returns to one resource are associated with returns to another. This covariance is consistent with what we would expect if a latent group characteristic (i.e., a general ability to use resources) is systematically driving returns to both resources. Finally, we find that the latent, general ability is associated with more coordinated attention, manifest via the "burstiness" (Riedl & Woolley, 2017) of group email communication.

Our novel approach to analyzing the ability of groups to transform resources into performance, and its relation to coordinated attention, has multiple implications. We extend research on intelligence at the individual (Schmidt, 2009; Schmidt, Hunter, & Outerbridge, 1986), group (Woolley, Aggarwal, & Malone, 2015a), and firm (Knott, 2008; Liebowitz, 2000; March, 1999; Wilensky, 1967) levels to suggest that the discovered general ability to use resources reflects a latent collective intelligence factor. This allows us to develop a provisional elaboration of the theory of collective intelligence with respect to unpacking what characterizes a smart team. In doing so, we contribute to classic theory on group process gains (Hackman & Morris, 1975; Larson, 2010; Steiner, 1972; Thompson, 2008) to suggest that teams that transform resources into greater performance than expected (achieving process gains) can be characterized as highly collectively intelligent. We further show that this ability is associated with coordinated attention. Finally, our empirical approach suggests a new way to look at capability, as a function of variation in effects across entities (such as groups, in this case) rather than the dominant approach of examining average effects.

GROUP RESOURCE USE

Research on group performance has maintained a longstanding focus on the importance of groups' ability to use available resources. Tracing back to early research on groups, Steiner (1972) introduced the theory that group productivity is determined by a group's potential (i.e., the resources that are available and relevant to the task demands) minus process losses (group interactions that are harmful). Other researchers later added the term "process gains" to account for group interactions that are helpful (Hackman & Morris, 1975; Larson, 2010; Thompson, 2008):

$$\text{Performance}_i = \beta_0 + \beta_1 \text{Potential}_i + \beta_2 \text{ProcessGains}_i - \beta_3 \text{ProcessLosses}_i + \varepsilon_i \tag{1}$$

Based on this theory, a group could do equally as well as the sum of its parts (i.e., process losses and gains net to zero), or it could do better or worse than the sum of its parts. A key insight is that, given some set of resources, groups can vary in the extent to which they capitalize on their resources relative to other groups with the same resources. Similarly, Hackman and Katz (2010: 1214) suggested that whether groups achieve their potential "all depends on the degree to which the group has, *and uses well* [emphasis added], the full complement of resources that are required for exceptional performance." This focus on resource use to explain performance emerges in another tradition as well: the influential inputs–processes–outputs, or I–P–O, model (Ilgen, Hollenbeck, Johnson, & Jundt, 2005; McGrath, 1984). In this case, inputs (resources) are hypothesized to have a causal influence on downstream processes (group interactions), which, in turn, influence the group's outcome (performance).

However, research has tended to empirically mask possible variance in group ability to use resources. As discussed above, much of the research on groups has examined an average effect of resources, such as the team's labor (e.g., number of "noncore contributors" [Cummings & Pletcher, 2011]), physical capital (e.g., technology [Choi, Lee, & Yoo, 2017]), or human and social capital (Faraj & Xiao, 2006; Gardner et al., 2012; Oh, Chung, & Labianca, 2004; Reagans, Argote, & Brooks, 2005). For example, Faraj and Sproull (2000) examined the effects of having expertise on performance. In doing so, they also considered the effect of coordination. With this second component, their work importantly demonstrated that coordination of resources significantly explains variance in group performance above and beyond merely accounting for the resources themselves (in their case, expertise). Yet, by estimating an average effect of expertise, this approach still assumes that expertise will have the same, rather than heterogeneous, effects for all groups. Similar examinations of average effects have been conducted in other studies of the coordination (Lewis, 2004; Liang, Moreland, & Argote, 1995), elaboration (van Knippenberg et al., 2004), pooling (Gigone & Hastie, 1993; Stasser & Titus, 1985), and integration (Gardner et al., 2012; Okhuysen & Eisenhardt, 2002; Tzabbar & Vestal, 2015) of group member knowledge. In such studies, resources have often been treated as inputs that could drive the group process (following the I–P–O model), but again, such an approach continues to mask variance across groups by focusing on average effects.

That said, one way in which researchers have explored variance in group use of resources has been to examine moderating conditions. For example, the effect of various resources on team performance can hinge on actions such as perspective-taking (Hoever et al., 2012) and collaboration (Boone & Hendriks, 2009; Woolley et al., 2008), or other factors that are thought to alter group interactions, such as network structure (Funk, 2014; Sherf, Sinha, Tangirala, & Awasty, 2018), social identity (Kane, 2010), or CEO characteristics (Buyl, Boone, Hendriks, & Matthyssens, 2011), among other factors. At the heart of this work is the idea that characteristics of the group or group interactions can influence the extent to which the group will be able to transform resources into output. For example, Tzabbar and Vestal (2015) argued that relationship strength among team members affects the cognitive ability and motivation to exchange information, thus affecting the extent to which the team will capitalize on that available information. In this way, contingency approaches are theoretically consistent with the notion that the effect of a group's resources on its performance is determined by the group's ability to use those resources.

However, contingency approaches, too, have limits. First, when estimating an interaction effect (i.e., moderation), the marginal effect of the resource on performance is assumed to be explained exactly by the moderating factor. This masks any group-specific variance in the transformation of the resource that could be attributed to other, even unobserved, factors. Second, contingency approaches tend to focus on moderation of a *single* resource. Yet, groups might exhibit a general ability to use resources—a characteristic of the group that systematically drives the returns to *all* resources.

Research on general abilities—ranging from dynamic capabilities (Schilke, Hu, & Helfat, 2018) to architectural competence (Henderson & Cockburn, 1994) to intelligence (Knott, 2008; Woolley, Chabris, Pentland, Hashmi, & Malone, 2010)—has often posited that a group's or a firm's general ability manifests in its use of all available resources (e.g., for a discussion of the role of intelligence in the use of all available resources, see Woolley et al., 2015b). Put differently, and applying measurement theory (Edwards & Bagozzi, 2000), the extent to which a group uses its resources could serve as a measure of the group's general ability. Taking this approach—assessing a general ability using an indicator—offers an advance to the research on general abilities. The latent nature of such a general ability has led to the development of laboratory tests (Levine, Bernard, & Nagel, 2017; Woolley et al., 2010), while in field settings, where current tests may not be feasible to implement, researchers have relied on qualitative work or proxy variables (Schilke et al., 2018). If organizational teams exhibit a general ability to use resources, understanding how to assess this in organizational teams could aid in resource-allocation decisions, while understanding the ability itself could shed light on how to better cultivate effective teams.

To build on past research and explore group variance in resource use, we implement an econometric approach (an RCM) that has been used, and advocated for, in strategy research. We empirically examine whether groups vary in the extent to which they convert resources into performance, while also exploring (a) whether this group-specific variance in transformation of resources is systematic across multiple resources, suggesting evidence of an unobserved, general ability; and (b) what is associated with that ability—the topic to which we next turn.

RESOURCE USE THROUGH COORDINATED ATTENTION

Recent research has noted that organizational teams face a heightened need to manage their attention (Bernstein, Leonardi, & Mortensen, 2017). Partly underlying this need may be the role of attention in managing resources. For a group to apply a relevant resource to the work at hand, members must manage their attention to others to coordinate their collective resources across various tasks, avoiding delays and missed opportunities. It follows that managing attention in a way that allows the team members to effectively apply those available resources should amplify the effects of those resources on team performance.

Of specific interest is the notion of joint, or coordinated, attention. Research from developmental psychology has suggested that a key factor in a dyad's ability to coordinate is their joint attention: when both partners, together, know "that they are attending to the same thing" (Carpenter & Liebal, 2012: 159). When dyads engage in joint attention, the individuals are not merely attending to the same thing but they know that they are both attending to that thing. Further, joint attention is important for reaching a shared intentionality, whereby people coordinate information and collaborate toward achieving a goal (Tomasello, Carpenter, Call, Behne, & Moll, 2005).

The idea that coordinated attention impacts a team's ability to capitalize on available resources has been supported in the management literature, too. For example, coordinated attention reflected in group members' facial synchronization has been shown to predict the group's collective intelligence in terms of its ability to perform consistently across a variety of tasks (Chikersal, Tomprou, Kim, Woolley, & Dabbish, 2017). Similarly, temporally "bursty" (Barabási, 2005) communication within a group can indicate that group members are synchronizing their attention to one another; in a study of geographically dispersed teams working on software programming projects, burstiness of team activity was shown to be positively related to performance (Riedl & Woolley, 2017). In contrast, research on the lack of coordinated attention, or asynchronous communication patterns, such as those characterized by interruptions and long delays (McGrath, 1991), has suggested that uncoordinated attention can lead to confusion, conflict, and misinterpretations (Cramton, 2001; Montoya-Weiss, Massey, & Song, 2001).

In sum, extant work has suggested that coordinated attention may allow for relevant information to be shared and for the communicators to better understand who is going to do what, such that teams with greater coordinated attention will also exhibit better transformation of resources into performance.

EMPIRICAL APPROACH

We seek to examine whether groups exhibit heterogeneity in the extent to which they convert resources into output, and whether this variance is systematic. We execute this by building on a model promoted in the strategy literature, which allows for examination of heterogeneity in the effects of inputs: a linear RCM, also known as a mixed-effects model with varying slopes or a mixed-effects model with random slopes (Alcácer et al., 2018; Knott, 2008). An RCM is a generalization of a hierarchical model that includes at least one coefficient that is not fixed and instead varies—for example, by group. This varying coefficient is comprised of two components: a mean effect on the outcome and a randomly distributed component that varies for each sampling unit—for instance, groups (Alcácer et al., 2018; Swamy, 1970; Swamy & Tavlas, 1995). In this way, the model allows for group-specific heterogeneity in slopes—that is, heterogeneity in resource use. While the inclusion of only fixed effects or random intercepts would mask group heterogeneity in resource use, an RCM allows for examining group-specific variance in the marginal effects of resources (our aim).

We specify our RCM as a linear regression model with panel data for observations *i* from groups *j*, with random coefficients for resource inputs (see "Methods" section for details on the current context and variables) as well as the intercept. We use this model to explore two possibilities. First, this model does not impose heterogeneity but allows for it based on the data. If there is substantial heterogeneity in the random coefficients of resource variables, this would suggest that there is group heterogeneity in the ability to capitalize on resources that is unaccounted for by the control variables in the model. We explore this by examining whether accounting for heterogeneity in returns to resources improves predictions of group performance above and beyond accounting for other individual, group, or context features. To do so, we compare the fit of the RCM delineated in Equation (2), below, to the fit of a model without random coefficients, but with random intercepts. An improved fit will indicate that, all else being equal, accounting for group differences in resource use adds to our ability to predict performance. This would suggest that there is substantial variance in returns to resources that can help to explain group performance. Additionally, following Knott's (2008) approach to quantify the extent to which there is heterogeneity in resource use, we calculate the number of groups for which the random coefficients for the resource variables statistically significantly differ from the mean. The second possibility we explore is whether there is positive covariance in the random effects. Such positive covariance would suggest a latent factor that systematically underlies the returns to multiple resources (Alcácer et al., 2018); this would suggest that groups exhibit a general ability to use a variety of resources. We use the following model for observations *i* from groups *j*, and resources 1, 2, …, *n*:

Level 1:

$$\text{Performance}_{ij} = \alpha_{0j} + \alpha_{1j}\text{Resource1}_{ij} + \alpha_{2j}\text{Resource2}_{ij} + \beta_3 X_{ij} + \varepsilon_{ij}$$

Level 2:

$$\begin{aligned} \alpha_{0j} &= \beta_{00} + \eta_{00j} \\ \alpha_{1j} &= \beta_{10} + \eta_{10j} \\ \alpha_{2j} &= \beta_{20} + \eta_{20j} \end{aligned} \tag{2}$$

where β_3 is a vector of coefficients and X is a matrix of control variables for observations *i* from groups *j*.

Finally, we explore the role of coordinated attention in the general ability to use resources. To do this, we take two approaches. First, we calculate the group's general ability to use resources as the average of the two (standardized) random slopes. We can then regress this score on predictors including measures of coordinated attention and other potential explanations. Second, as a robustness test, we take advantage of another feature of RCMs: a prediction of the random coefficients can be modeled as a second level in the multilevel regression (Gelman & Hill, 2007: 280–283). Specifically, we estimate a model in which the random coefficients for the resources are predicted by coordinated attention. Note that one benefit of the RCM is that this second level of analysis (in which we estimate the random slopes for each group) can be done simultaneously with the prior level (estimating the outcome variable for each group at each time). This is done by including a cross-level interaction (Gelman & Hill, 2007: 280–283). In our case, we include interactions between the resource variables and coordinated attention, such that we can obtain estimates of how coordinated attention affects the slopes for those resources (i.e., returns to those resources). In contrast, estimates of the fixed effect of the coordinated attention variable are interpreted as estimates of its effect on the random intercept. We use the following RCM for observations *i* from groups *j* (see Figure 1 for visualization of conceptual model using specific context variables described in the "Methods" section):

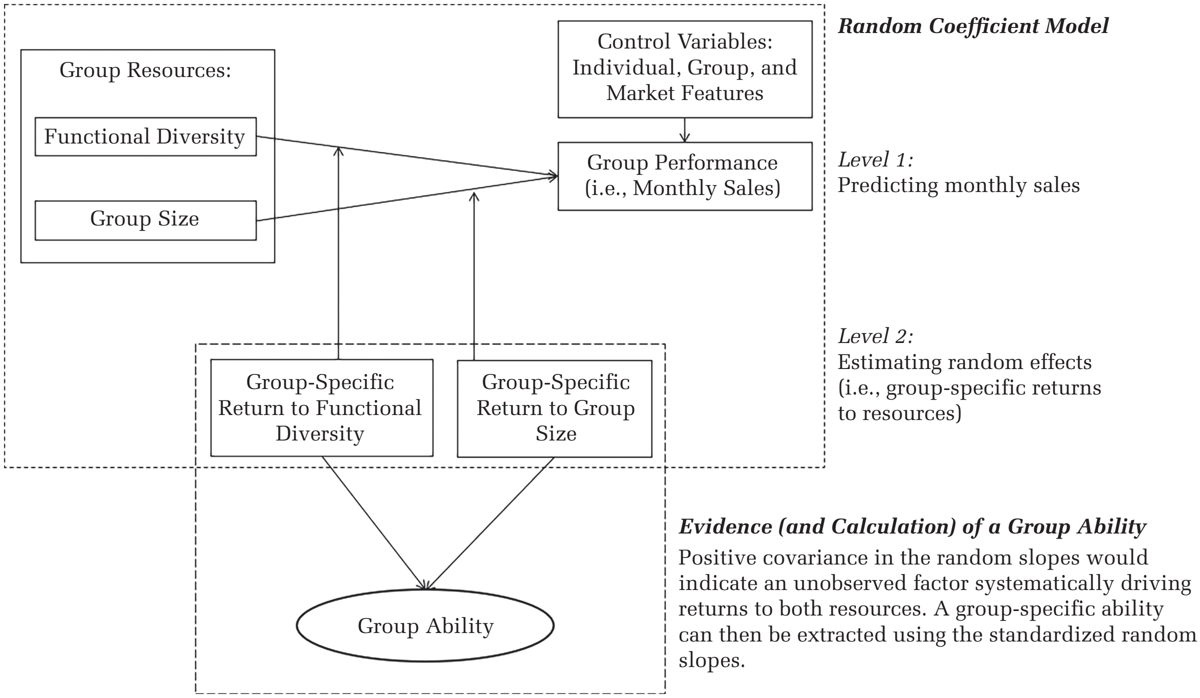
Level 1:

$$\text{Performance}_{ij} = \alpha_{0j} + \alpha_{1j}\text{Resource1}_{ij} + \alpha_{2j}\text{Resource2}_{ij} + \alpha_{3j}\text{ResourceN}_{ij} + \beta_3 X_i + \varepsilon_{ij}$$

Level 2:

$$\begin{aligned} \alpha_{0j} &= \beta_{00} + \beta_{01} C_j + \eta_{00j} \\ \alpha_{1j} &= \beta_{10} + \beta_{11} C_j + \eta_{10j} \\ \alpha_{2j} &= \beta_{20} + \beta_{21} C_j + \eta_{20j} \end{aligned} \tag{3}$$

FIGURE 1
Visualization of Conceptual Model for Derivation of a General Group Ability to Use a Variety of Resources



Notes: Group resources in a given month are expected to have an average effect on group sales for that given month; however, groups may also vary in their returns to those resources (i.e., variance in the group-specific returns to the resources). Further, evidence of a latent general ability to use resources would come from consistent returns to a variety of resources (i.e., positive covariance of the estimated team-specific returns). Given such evidence, a general ability score can be calculated for each sales group based on the average of the standardized random slopes, as extracted from the random coefficients model.

where β_3 is a vector of coefficients and X is a matrix of control variables for observations i from groups j; and where β_{01} is a vector of coefficients and C_j is a matrix of coordinated attention and other control variables for groups j, β_{11} is a vector of coefficients and C_j is a matrix of coordinated attention and other control variables for groups j, and β_{21} is a vector of coefficients and C_j is a matrix of coordinated attention and other control variables for groups j.

METHOD

Data and Context

We use a nine-month panel (August 2015–April 2016) of 1,365 retail-banking sales groups from a national financial institution operating in the United States. Sales groups are identified as a group of retail sales personnel who are colocated. These sales groups are included in the sample if there are consistently two or more sales personnel working in the location; sales groups in the sample ranged from 2 to 17 members.

Author's Voice:
How did you get access to your data or site?

The primary measure of performance in this setting is the sales revenue generated, which comes from the services the employees supply to clients (e.g., checking and savings accounts, credit cards, and mortgages). Sales-group members are tasked with bringing in sales by generating new customers, as well as maintaining current clients and increasing the products and services provided to those extant clients. Despite the traditionally individualistic structure of this type of work, research has revealed that working collectively is increasingly important to the viability of financial and professional service firms (Ahearne et al., 2010). For example, qualitative research on similar sales teams has highlighted that member interactions and collective work are important features of sales teams' work (Aime, Humphrey, DeRue, & Paul, 2013). Additionally, in the current study's context, the sales-group members receive bonus pay based both on individual performance as well as the entire group's collective performance. Sales-group members in this context thus have some structural incentive to work together. Further, as an indication of the interactive and even interdependent nature of the current context, informants at the national headquarters office emphasized the need for sales-group members to work together to exchange referrals, share knowledge about the expansive number of products and services available to clients, and so on. This notion was corroborated in our own interviews with sales personnel in a subsample of 12 sales groups, in which members discussed working with fellow group members. For example, interviewees discussed going to group members for specialized knowledge, to make referrals, or to exchange information about products. Multiple employees referred to their work as "collaborative" or to their group as a "team." Together, this evidence suggests that sales-group members in this context can and do work in an interdependent fashion. We thus believe the retail-banking sales groups in this sample to be relevant to the study of group resource use.

Group Performance Measure

Monthly sales. To measure group performance, we calculate, for each group in each month, the sum of group members' sales. We use the log transformation of this number in our analyses.

Resource Measures

In this paper, we focus on two key resources: functional diversity and group size.[2]

Functional diversity. We account for the group's *functional diversity* in terms of the group members' role specialization. Specifically, we calculate the percentage of group members working in specialist roles versus general sales roles. We do this for each group, for each month. In 31% of the sample groups, group functional diversity varied over time. This within-group variance allows for exploring whether groups differ in their ability to gain more sales from more functional diversity. We center the measure of functional diversity by the group mean, following recommendations for the estimation of cross-level effects (Aguinis, Gottfredson, & Culpepper, 2013).

Group size. We calculate the group's size as a simple count of the sales-group members in a given month. We do this for each group, for each month. In 77% of groups, the group experienced variance in group size over time. This within-group variance allows for exploring whether groups differ in their ability to gain more sales from more labor, as assessed by group size. We center the measure of group size by the group mean, following recommendations for the estimation of cross-level effects (Aguinis et al., 2013).

Coordinated Attention Measure

To capture coordinated attention, we use archival data on email activity among sales-group members. We build on prior work (Riedl & Woolley, 2017) to examine coordinated attention by measuring the *email burstiness* within the group—that is, how temporally clustered the emailing was as opposed to being uniformly distributed across time. Each group received a single measure based on the burstiness of its email activity over the entire observation period.

We believe email activity offers a reasonable indicator of coordination within the group for two reasons. First, we build on research that has demonstrated a positive correlation between face-to-face and email communication (Dabbish & Kraut, 2006). Second, we draw from our particular context; we conducted a series of interviews as part of a separate study. Those interviews revealed that emails were used more frequently when contacting someone outside of the group than within; however, emails were used within the group to coordinate. In this setting, employees were frequently busy with different customers during business hours or attending different meetings, often making it difficult to pass information or ask questions using verbal communication in real time. Consequently, employees communicated frequently via email to share referrals, inquire or share information about the vast number of products and services the organization offered, and to hand off information. In sum, our interviews suggest that by examining email interaction, we are capturing a significant portion of the

[2] Models including more than two random slopes are subject to a challenge in estimating the covariance parameters (Gelman & Hill, 2007). To avoid this challenge and any bias to our estimation of covariance in our random slopes, we restrict our analyses to explore the variance and covariance of only two random slopes in our model. That said, results reported here are robust to treatment of any two of the following five variables as the focal resources: group size, functional diversity, group experience working together (100% of groups experienced variance in this variable), average organizational experience (100% of groups experienced variance in this variable), and average salary (98% of groups experienced variance in this variable). Other available variables that could be characterized as resources or indicators of resources (e.g., measures of physical capital such as market position) are static in our sample; the lack of within-group variance in these variables prevents us from exploring group-specific effects of those variables on performance.

communication among employees used to manage coordination.

To measure email burstiness, we first calculate the time elapsed between any within-group email, in seconds. We then calculate both the standard deviation (*SD*) and the mean of this elapsed time. From this, we calculate a raw burstiness measure using the following formula: Burstiness = [(*SD* – mean) / (*SD* + mean)]. This raw score ranges from 1 to –1. Numbers closer to 1 indicate greater clustering into bursts, while numbers closer to –1 indicate a more even dispersion of emailing over time. Note that this yields a single measure for each group. We calculate this measure at the group level (rather than for each group in each month) to allow for modeling the effect of this variable on resource use in the second level of the estimated RCM.

It is possible that the burstiness of a group's emailing is affected by the overall number of emails sent within the group. Statistically, the more emails a group sends the more potential there is for those emails to be distributed into temporal clusters. To account for this, we follow prior research (Riedl & Woolley, 2017) and standardize the measure using a bootstrapping approach. This approach calculates a *z*-score that is based on the group's raw burstiness score and adjusted for what we could expect given the total number of emails sent. We determine an expected burstiness score for each group using the following simulation approach. We first generate 1,000 random samples of size *n* (where *n* = the total number of emails sent by the group) from the set of all emails sent by all groups (used as realistic set of email times). We can then take the mean and *SD* of these bootstrapped scores as indications of what we could expect based on the *n* number of emails sent. Finally, we calculate a *z*-score for the group using the formula: [(raw burstiness – mean bootstrapped burstiness)/ *SD* bootstrapped burstiness]. We use this standardized measure of burstiness in our analyses.

TABLE 1
Descriptive Statistics for 12,079 Observations from 1,365 Sales Groups

Variable	Mean	*SD*
Monthly sales[a]	141,696.77	133,372.54
Functional diversity[a]	7.98	13.14
Group size[a]	3.56	1.38
Average organizational tenure	64.32	61.24
Experience working together	9.67	6.40
Average base salary[a]	10,160.98	5,107.35
Percent women[a]	53.72	21.55
Age diversity	10.12	5.61
Rate of members gained	5.43	14.54
Rate of members lost	3.41	8.79
Prior performance[a]	41,066.57	30,008.15
Group rating	2.02	0.77
Market FDIC deposits	372,727.00	229,445.00
Email burstiness	5.04	4.91
Average monthly emails	30.79	25.36

Notes: For each sales group, the email measures represent the sale group's email communication patterns throughout the entire period of observation. Thus, there are only 1,365 observations of the email variables.

[a] Scaled by a constant to help mask the identity of the financial institution.

Control Variables

Group composition. We control for a variety of factors related to the group's composition. For each of these variables, we measure the variable in each group, in each month. We measure the group's *age diversity* as the *SD* of group members' ages. We measure the group's *sex composition* as the percentage of women in the group out of the group size. We calculate the group's *organizational tenure* as the average number of months for which group members have been working in the institution (in any position), centered by the group mean. We also account for group members' *experience working together* by measuring the average dyadic tie between group members, where a tie represents the number of months for which two individuals have worked together in the given group (Reagans & Zuckerman, 2001), centered by the group mean. Finally, we include the *average salary* received by sales-group members, which is also centered by the group mean.

We control for *prior performance*, assessed as the average individual sales from the prior month. We use the log transformation of this number in our analyses.

We account for turnover in terms of two separate components: gaining and losing group members. To do so, we calculate two measures. First, the *rate of members gained* is calculated as the percentage of group members gained during a given month relative to how many members worked in that group in the prior month. Second, the *rate of members lost* is calculated as the number of members lost during a given month relative to how many members worked in that group the prior month. In taking this approach to examine the rate of turnover, we follow norms from prior research (e.g., Ton & Huckman, 2008; Wegner, 1986). However, we also focus on membership gains and membership losses separately, rather than general changes to the group size. In this way, a four-person group that gains one member and loses one member in a month will stand out as different from a four-person group with no membership change.

TABLE 2
Variable Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Monthly sales														
2	Functional diversity	.46*													
3	Group size	.53*	.20*												
4	Average organizational tenure	.08*	.08*	−.17*											
5	Experience working together	.10*	.15*	−.19*	.49*										
6	Average base salary	.20*	.34*	−.05*	.34*	.40*									
7	Sex composition	−.12*	−.22*	−.14*	.28*	.12*	.00								
8	Age diversity	.06*	.06*	.01	.29*	.07*	.07*	.10*							
9	Rate of members gained	−.03*	−.01	.12*	−.13*	−.32*	−.09*	−.07*	−.01						
10	Rate of members lost	−.02+	.03*	.11*	−.10*	−.14*	−.05*	−.06*	−.02+	.04*					
11	Prior performance	.55*	.46*	.04*	.18*	.22*	.25*	−.07*	.08*	−.01	−.03*				
12	Group rating	.05*	.00	.03*	.02*	.02*	.01	−.03*	.05*	−.01	.01	.04*			
13	Market FDIC deposits	.17*	.16*	.16*	−.14*	−.08*	.00	−.14*	−.02	.04*	.04*	.12*	−.02*		
14	Email burstiness	−.19*	−.09*	−.17*	−.07*	−.07*	−.07*	.01	−.05*	.04*	.06*	−.11*	−.01	−.01	
15	Email monthly average	.21*	.20*	.08*	.06*	.07*	.13*	.04*	.03*	−.04*	−.03*	.19*	.01	.05*	−.21*

+ $p < .10$
* $p < .05$

Ability. We capture ability using the *group rating* given to each group by the financial institution's headquarters office based on 2014 group performance relative to expectations (1 = below expectations, 2 = meets expectations, 3 = exceeds expectations). This was the final year the institution made such an evaluation. This group rating is static over time.

Effort. We control for the *total amount of email communication* as the average number of emails sent per month among group members over the duration of the nine months included in the study. We use the log transformation of this number in our analyses. This measure of effort is therefore static over time.

Leadership. We include dummy variables for each group's regional manager. These indicators do not vary over time unless the regional manager changed.

Market factors. We control for a variety of market and environmental features. First, to account for possible seasonality effects, we include dummies for the financial *Quarter* (Jan.–Mar., Apr.–Jun., Jul.–Sep., and Oct.–Dec.). We also include indicators of the market that are time-invariant. To control for market capacity, we include measures of 2014 *FDIC deposits* within the group's zip code. We use the log of these deposits in our analyses. This value is static over time. We also control for the *location* type (e.g., whether the sales-group location is stand-alone or embedded in another store). The type of location is an indicator that is static over time.

Author's Voice:
What was the most difficult or challenging aspect of this research project and paper?

RESULTS

Descriptive statistics of, and correlations among, study variables are presented in Tables 1 and 2. To estimate RCMs, we use the lmer function in the lme4 package in *R*,[3] estimated with MLE (Bates, 2005).[4]

Variance in Resource Use

We explore whether there is evidence of heterogeneity in the extent to which groups capitalize on resources, as assessed via the slopes of functional diversity and group size. We also test whether groups achieve returns to those resources in a systematic way, such that there is positive covariance of the slopes. To do so, we estimate multiple models for comparison: a null model including random intercepts only (Table 3, Model 1), a model including random intercepts and control variables (Table 3, Model 2), and our focal model, which includes random intercepts and random slopes for functional diversity and group size, as well as control variables (Table 3, Model 3).

[3] See Appendix A for *R* code.

[4] Examination of the auto-correlation function (using the acf function in *R*) reveals no auto-correlation among residuals; therefore, no adjustments to the correlation structure in the model were made.

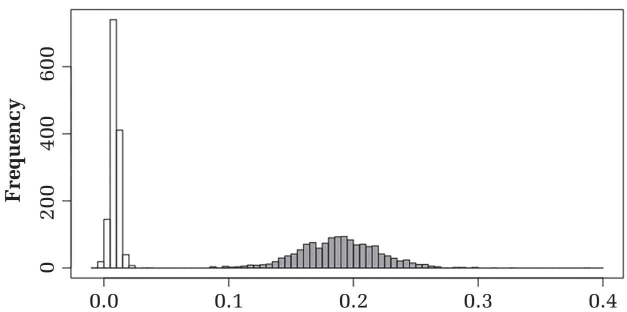
TABLE 3
Estimating Monthly Sales

Variable	Model 1: Random Intercept Only	Model 2: Random Intercept and Controls	Model 3: Random Intercept, Random Slopes, and Controls	Model 4: Prediction of Random Slopes
Resources				
Functional diversity		0.008***	0.009***	0.009***
		(0.001)	(0.001)	(0.001)
Group size		0.186***	0.189***	0.169***
		(0.008)	(0.009)	(0.012)
Effect on resource slopes				
Email burstiness ×				0.000
Functional diversity				(0.000)
Email burstiness ×				0.004*
Group size				(0.002)
Controls				
log(prior performance)		0.069***	0.058***	0.059***
		(0.009)	(0.009)	(0.009)
Sex composition		–0.001***	–0.001***	–0.001***
		(0.000)	(0.000)	(0.000)
Age diversity		0.003*	0.003	0.003
		(0.002)	(0.002)	(0.002)
Rate of members gained		–0.001***	–0.001***	–0.002***
		(0.000)	(0.000)	(0.000)
Rate of members lost		–0.003***	–0.003***	–0.003***
		(0.000)	(0.000)	(0.000)
Group rating		0.066***	0.068***	0.065***
		(0.019)	(0.019)	(0.019)
log(market FDIC deposits)		0.115***	0.118***	0.119***
		(0.020)	(0.020)	(0.020)
Experience working together		0.009***	0.009***	0.009***
		(0.002)	(0.002)	(0.002)
Avg. organizational tenure		0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
log(email monthly average)		0.279***	0.280***	0.259***
		(0.023)	(0.023)	(0.022)
log(average base salary)		0.227***	0.230***	0.229***
		(0.016)	(0.017)	(0.017)
Location type		–0.100*	–0.099*	–0.083*
		(0.039)	(0.039)	(0.039)
Email burstiness				–0.024***
				(0.003)
Constant	11.771***	8.053***	8.134***	8.244***
	(0.018)	(0.333)	(0.335)	(0.328)
ICC	0.64			
Random effects: variance (*SE*)				
Intercept	0.429	0.232	0.238	0.226
Functional diversity			0.0001	0.0001
Group size			0.004	0.004
Residual	0.246	0.193	0.189	0.189
Fixed effects				
Quarter	No	Yes	Yes	Yes
Regional manager	No	Yes	Yes	Yes
BIC	21,191	19,660	19,643	19,605
Number of estimated parameters	3	202	207	210
Pseudo-R^2	0	0.371	0.364	0.382

* $p < .05$
** $p < 0.01$
*** $p < 0.001$

We first find that the groups account for a substantial amount of variance in sales (ICC = .64; Table 3, Model 1). We then find that the focal model (Table 3, Model 3; BIC = 19,643) is a better fit to the data than a random coefficients model that includes only random intercepts (Table 3, Model 2; BIC = 19,660; $\chi^2(5) = 64.2$, $p < .001$). These results indicate that accounting for group variance in returns to resources explains significant variance in group performance above and beyond that explained by the observed individual, group, and market features. In other words, this evidence indicates that there is significant variance in group resource use.

FIGURE 2
Overlapping Histogram of Random Slopes Estimates



White: Functional Diversity: Dark Grey: Group Size

Next, we examine the heterogeneity in resource use in our focal model. We find that, on average, functional diversity is positively associated with sales ($\alpha_{1j} = 0.01$, $p < .001$). However, taking together B_{10} and η_{10j}, we find variation across groups in the effect of functional diversity on sales (random coefficient variance = 0.0001; *SD* = 0.009; see Figure 2 for histogram depicting variance in the two random slopes). Following Knott (2008), we use one-sample *t*-tests—[$(B_{10} - \eta_{10j})$ / $SE(\eta_{10j})$] with a Bonferroni correction—and find that 611 out of the 1,365 groups (44.8%) have returns to functional diversity that significantly differ from the mean. Interpreting these results, groups, on average, achieve 20% more sales from having 20% more functional diversity. However, groups achieving a return 1 *SD* below average return as low as a 0% change to sales from the same 20% increase in functional diversity, while groups achieving a return 1 *SD* above average could see 40% more sales given the same 20% increase in functional diversity.

We also find that, on average, increases in group size increase sales ($\alpha_{2j} = 0.19$, $p < .001$). However, taking together B_{20} and η_{20j}, we find variation in the effect of group size (random effect standard deviation = 0.004; *SD* = 0.065). Following Knott (2008), we

TABLE 4
OLS Predicting Group Resource-Use Ability (Derived from Random Slopes for Functional Diversity and Group Size)

	Model 1	Model 2	Model 3
Constant	-0.179^{**}	-0.631^{**}	-0.429^{*}
	(0.013)	(0.206)	(0.209)
Email burstiness	0.034^{**}	0.039^{**}	
	(0.002)	(0.002)	
Email monthly average		0.013	−0.022
		(0.014)	(0.015)
Market FDIC deposits		0.044^{**}	0.045^{**}
		(0.013)	(0.013)
Location type		0.050^{*}	0.073^{**}
		(0.025)	(0.025)
Group rating		0.024^{+}	0.019
		(0.012)	(0.013)
Fixed effects			
Quarter	No	Yes	Yes
Regional manager	No	Yes	Yes
Observations	12,079	12,079	12,079
R^2	0.03	0.09	0.06
Adjusted R^2	0.03	0.08	0.05
Residual *SE*	0.99	0.96	0.98
F	351.70^{**}	6.26^{**}	4.09^{**}
	(*df* = 1; 12,077)	(*df* = 190; 11,888)	(*df* = 189; 11,889)

+ $p < 0.1$
* $p < 0.05$
** $p < 0.01$

use one-sample *t*-tests—$[(B_{20} - \eta_{20j} / SE\,(\eta_{20j})]$ with a Bonferroni correction—and find that 619 out of 1,365 groups (45.4%) have returns to group size that significantly differ from the mean. This suggests that, on average, groups achieve a 19% increase in sales from an increase of one group member. However, groups achieving a return 1 *SD* below average would see only 13% more sales with the same change in group size, while groups achieving a return 1 *SD* above average would see 25% more sales. Together, the model comparisons and the tests of resource-use heterogeneity suggest that groups do differ in their ability to reap returns to their resources.

Lastly, we build on Alcácer et al.'s (2018) recommendation to examine the relationship between the random slopes. We find that the random slopes have a positive covariance of .91, and are positively correlated ($r = .97$, $p < .001$). This positive covariance suggests evidence of an underlying, unobserved factor that is systematically affecting returns to group resources.

The Role of Coordinated Attention

We explore the relationship between resource use and coordination using two approaches. In our primary analysis, we first calculate a score for each group's general ability to use resources based on the random slopes from the focal model (reported in Table 3, Model 3). Specifically, we take the average of each group's standardized random effects to assess the group's general ability to use resources. We then regress those scores on the group's email burstiness (Table 4, Model 1). Results reveal that burstiness has a positive and significant association with the general ability to use resources ($B = 0.03$, $p < .001$). In a second model (Table 4, Model 2), we also control for other potential explanations of variation in returns to resources: effort (i.e., average monthly emails), market conditions (i.e., market FDIC deposits, type of location), ability (i.e., the group rating), and leadership (i.e., fixed effects for regional managers). Results reveal that the relationship between burstiness and the general ability to use resources holds ($B = 0.04$, $p < .001$.) above and beyond the effect of alternative explanations.

As a robustness test, we also take advantage of a feature of the RCMs, which is to model the random slopes. We first include only email burstiness as a predictor in the second level of the regression (i.e., predicting the random slopes). Results (Table 3, Model 4) reveal that this model fit (BIC = 19,605) is an improvement (relative to Table 3, Model 3, BIC = 19,643). Additionally, results reveal a positive interaction between email burstiness and group size ($B = 0.004$; $p = .016$) but not functional diversity ($B = 0.000$; $p = .760$). Given the model specification, the former and significant interaction signals the effect of the bursty emailing pattern on the *slope* of the group size. Thus, results indicate that groups engaging in burstier emailing also achieved greater returns to group size. This effect holds when including second-level controls for any effects of effort, market, ability, and leadership on the slopes of the resources.

DISCUSSION

A group's ability to capitalize on available resources is fundamental to its performance. Using an RCM and a large panel data set of financial sales groups, we find that groups exhibit systematic variance in the extent to which they transform resources into output. In this way, we offer evidence to support the theory of a *group-specific* ability to convert a *variety* of resources into output. This provides new insights that are masked by the standard approach of focusing on an *average* effect of a resource across groups or on the average moderating effect of a group feature on the relationship between a *single* resource and performance. Additionally, we find that this general, group-specific ability is associated with a group's coordinated attention, captured by the group's emailing burstiness. These findings have theoretical implications for research on collective intelligence, group resource use, and coordinated attention. They also have practical implications.

Author's Voice:
What is the social relevance of your research?

Collective Intelligence

The construct of intelligence has been tied to an ability to use resources effectively across research on individuals (Schmidt, 2009; Schmidt et al., 1986), groups (Woolley et al., 2015b), and firms (Knott, 2008; Liebowitz, 2000; March, 1999; Wilensky, 1967). For example, given the same knowledge (i.e., a resource), a smarter individual will be better able to use that knowledge and achieve better performance (Schmidt, 2009). Similarly, groups with high collective intelligence are thought to better "take advantage of the full knowledge and skills of all their members" (Woolley et al., 2015b: 422). At the organizational level, researchers have long argued that intelligence will be reflected in an organization's ability to make use of available resources (Knott, 2008; Liebowitz, 2000; March, 1999; Wilensky, 1967). Taking together the research on intelligence across levels of analysis, we believe that the theory of intelligence suggests that, all else being equal, a general collective intelligence factor systematically drives the extent to which a group transforms all types of resources into output. If so, this theory would predict that after accounting for ability, effort, leadership, and so on, we should find evidence of a general, latent factor (reflecting intelligence) that systematically influences resource use. Indeed, we find just such evidence in the current study.

To fully consider whether collective intelligence leads to resource use such that we can consider resource use as an indicator of intelligence, we consider four conditions that would support that claim (Edwards & Bagozzi, 2000). First, we note that the phenomenon should be distinct from its indicator. To this end, we note that collective intelligence is a phenomenon characterizing the group, and it is theoretically distinct from the extent to which the group transforms resources into performance.

Second, we examine convergent validity. Collective intelligence and the measure of the extent to which the group transforms resources into performance both covary with coordinated attention. Past work has measured collective intelligence using a Test of Collective Intelligence (Kim, Engel, Woolley, Lin, McArthur, & Malone, 2017; Woolley et al., 2010); based on the finding that teams exhibit consistent performance across tasks, this approach uses a team's scores across a battery of tasks to derive its collective intelligence score. Research in this tradition has demonstrated a relationship between collective intelligence and the group's tacit coordination and coordinated attention (Aggarwal, Woolley, Chabris, & Malone, 2019; Chikersal et al., 2017; Engel, Woolley, Jing, Chabris, & Malone, 2014; Woolley et al., 2010). Similarly, we find that the general ability to use resources (which we interpret as intelligence) is associated with coordinated attention. In other words, we find some convergent validity supporting the claim that a general ability to use resources reflects collective intelligence.

The third requirement to claim causality from collective intelligence to its indicator, resource use, is temporal precedence. Absent an experimental test in which collective intelligence is manipulated, we instead rely on theory. Collective intelligence has been demonstrated to exist (Engel et al., 2014; Woolley et al., 2010), develop quickly (Chikersal et al., 2017), and remain stable over time (Woolley & Aggarwal, 2020). Given the quick emergence and stability of collective intelligence, a group's behavior (e.g., use of resources) is likely to temporally follow the existence of its collective intelligence.

Lastly, we attempt to eliminate alternative explanations for the relationship between the construct collective intelligence and the measure of resource use. Specifically, we model the effects of leadership, effort, ability, and the group's market as predictors of resource use, but these variables are shown not to be significant predictors. At the same time, the variable that does significantly predict resource use is coordinated attention, a known covariate of collective intelligence (Chikersal et al., 2017).

In sum, the phenomenon of collective intelligence and the measure of resource use are distinct, they covary with coordinated attention, collective intelligence theoretically should precede resource use, and we have ruled out potential alternative explanations of the resource use ability. Together, we take this to be suggestive of field evidence of a collective intelligence factor that is manifest in resource use, and we see the contributions of this finding as twofold. First, future work may be able to use this empirical method of identifying variance in resource use as a means for continuing to unpack the phenomenon of collective intelligence. Second, this work has implications for the theory of collective intelligence. While some have debated the strength of the evidence of a general collective intelligence factor in teams (Credé & Howardson, 2017), more recent analyses and meta-analyses (Woolley, Kim, & Malone, 2018; Riedl, Kim, Gupta, Malone, & Woolley, 2021) have affirmed the evidence for it and its role in predicting future group performance. Our work suggests an extension of the theory of collective intelligence with regard to unpacking what it means to be a smart team—smart teams may consistently perform well in part because they can achieve greater-than-average returns to their resources.

We would be remiss if we did not acknowledge another general ability that has received great attention: dynamic capabilities (Schilke et al., 2018). However, we believe that dynamic capabilities and collective intelligence are complementary but distinct constructs. Dynamic capabilities refer to "the capacity of an organization to purposefully create, extend, or modify its resource base" (Helfat et al., 2007: 4) and to "achieve new resource configurations" (Eisenhardt & Martin, 2000: 1107). That is, the focus of dynamic capabilities research is on whether entities can alter their resources in order to adapt to a changing environment (Teece, Pisano, & Shuen, 1997). By contrast, rather than focus on changing what a team has, collective intelligence captures the ability to capitalize on what is given. Because our analysis examines the latter, the interpretation of collective intelligence seems more appropriate. Certainly, in practice the two are likely to be related; theory suggests that intelligence may well impact the ability to both use and modify resources, and future work could explore this.

Group Resource Use and Coordinated Attention

While our work has implications for research on collective intelligence, our collective-intelligence perspective also allows for a new way to think about how groups transform resources into performance. Namely, we think about transformation of resources as a process gain that differs from group to group, and we posit that the transformation of resources into greater performance than expected reflects higher collective intelligence. While a vast body of work has highlighted the importance of group processes, including how resources are pooled, integrated, and elaborated—in short, how they are used—our approach differs in that we conceptualize the use of resources in terms of an ability that differs across groups. In doing so, we assume systematic variance between groups, and our findings demonstrate that our approach adds value by explaining otherwise unexplained variance in group performance.

Additionally, the current work employs an empirical approach, which follows directly from our perspective on the transformation of resources as differing from group to group, and it offers a new way to measure both the transformation of resources and what facilitates that transformation. This empirical approach to accounting for, and unpacking, variance in how groups use resources has both practical and theoretical implications. First, the demonstrated benefit of the empirical approach used here has a practical implication for resource allocation decisions. In organizations with many teams working on the same or similar tasks, it may be prudent to determine the groups most likely to capitalize on firm resources. Additionally, understanding what allows for some teams to reap greater returns to their resources will shed light on how to facilitate more efficient work across all groups. An emerging theoretical focus in the study of resource use, particularly with regard to knowledge resources, is the beneficial role of managing attention (Chikersal et al., 2017; Riedl & Woolley, 2017; Tomprou, Kim, Chikersal, Woolley, & Dabbish, 2019). We add to this evidence, demonstrating that coordinated attention, captured via the burstiness of emailing, is associated with a group's ability to capitalize on its resources. Building from research on the benefits (detriments) of synchronous (asynchronous) communication, we suspect that a cognitive mechanism underlies the role of coordinated attention (Cramton, 2001; McGrath, 1991; Riedl & Woolley, 2017). That is, real-time, joint interactions may allow for a richer and more cognitively productive interaction, devoid of delays or misunderstandings. Yet, it is also possible that the association between burstiness and resource use could be driven by a relationship-oriented and even affective mechanism—people may feel better when colleagues respond quickly (compared to a delayed reply), and this positive affect (or absence of a negative affect) may fuel a greater willingness to work together versus avoiding future interactions. Future research could work to better understand the underlying mechanism of coordinated attention to inform the types of interventions that could cultivate better coordinated attention and thus better use of available resources. Of further consideration is the set of conditions under which coordinated attention is needed. Such attention management may be particularly important in teams with fluid, distributed, or overlapping membership, wherein conditions are created in which communication is more likely to become asynchronous. Coordinated attention is also likely to be more critical in teams that are highly interdependent, in which delays and misunderstandings would be more detrimental.

Limitations

There are several limitations to this research that offer directions for future research. First, our study highlights emergent relationships between what we believe to be evidence of collective intelligence and coordination, but neither past work nor the current study has demonstrated whether intelligence causes coordination, or vice versa, which raises numerous questions. For example, if we alter a group's communication pattern, can we raise the group's collective intelligence? To build on the current paper, two research directions in particular stand out. First, given the newness of the collective intelligence construct in the groups and teams literature, and the incipient but emerging finding of a relationship to coordination, qualitative work could help to unpack, more broadly, how collective intelligence develops and manifests in the workplace (Edmondson & McManus, 2007). Additionally, efforts at intervention could help to uncover just how the phenomenon works. While initial evidence suggests that collective intelligence is fairly stable over time (Woolley & Aggarwal, 2020), building on established relationships between coordination and collective intelligence to identify methods for developing collective intelligence (or providing scaffolding to make up for low collective intelligence) could greatly aid organizations in the effort to cultivate smarter teams.

Second, we explored potential alternative explanations of the systematic returns to resources including effort, leadership, ability, and market conditions. Yet these tests come with limitations. For example, to account for a group's effort, we control for overall emailing. This is a crude proxy, and future work could examine more precisely the role of factors such as effort, motivation, or engagement. Still, while these factors might impact a group's resource use because teams with more motivation (for example) are more likely to try to use their resources, we note that even when members are motivated to work together there is a question of whether they are cognitively able to do so. Future work could further disentangle how these affective and cognitive components relate to an ability to use resources. Similarly, to account for the potential role of leadership, we include fixed effects for groups' regional managers. This, too, is a crude proxy and does not rule out that local leadership—the group's leader—could underlie the ability to capitalize on resources. For example, a leader could direct the team members' attention (Larson et al., 1996) such that leadership impacts ability to use resources. Future work could take a finer-grained approach to understanding the relationships between leader behaviors, coordinated attention, and resource use.

Additionally, we assess coordinated attention using a measure of email burstiness that is derived from the entire observed time period. This constraint to modeling burstiness at the second level of the regression is an artifact of our decision to use a random coefficients model. While this approach is informative, it also inhibits our ability to examine the dynamic nature of communication patterns. Future research could explore whether behavior that describes "smart" coordination changes depending on the context.

CONCLUSION

Groups are frequently used in today's organizations and their effectiveness relies not only on their potential but on their ability to collectively utilize available resources. We offer a new perspective on the transformation of resources into performance, suggesting and demonstrating that groups vary in their ability to use resources. In doing so, this work suggests elaborations to the theory of collective intelligence that we hope will spur future research on the phenomenon to better explain group performance, as well as the role of coordinated attention.

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APPENDIX A *R* CODE

```
##############################################################
### CREATION OF STANDARDIZED BURSTINESS MEASURE (BZ) ###
##############################################################

### load packages ###
library(reshape)
library(data.table)
library(foreach)
library(dplyr)

### load all email data, with each row representing one email ###
EmailData <-read.csv("filepath.csv")
#variables…
#T1 = the time the email was sent (year, month, day, hour, seconds)
#Note that T1 should be in chronological order
#group = group identifier (i.e., the group in which the email was sent and received)

### Score raw burstiness for each group ###
#calculate the time difference between emails within a group
EmailDataV2<-EmailData %>% group_by(group) %>% mutate(T0=lag(T1,1))
EmailDataV2$TimeDiff<-EmailDataV2$T1-EmailDataV2$T0
#calculate the mean and sd of time differences for each group
TimeDiffMean<-aggregate(TimeDiff~group,data=EmailDataV2, FUN= "mean")
colnames(TimeDiffMean)[colnames(TimeDiffMean)=="TimeDiff"]<- "mean_TimeDiff"
TimeDiffSD<-aggregate(TimeDiff~group,data=EmailDataV2, FUN= "sd")
colnames(TimeDiffSD)[colnames(TimeDiffSD)=="TimeDiff"]<- "sd_TimeDiff"
GroupTimeDiffStats=merge(TimeDiffMean,TimeDiffSD,by="group")
#calculate a raw burstiness score
GroupTimeDiffStats$RawBurstiness<- (as.numeric(GroupTimeDiffStats $sd_TimeDiff - GroupTimeDiffStats $mean_TimeDiff))/(as.numeric((GroupTimeDiffStats $sd_TimeDiff + GroupTimeDiffStats $mean_TimeDiff))

### load helper functions ###
#load function to compute time intervals between emails
getTimeIntervals<-function(x) {
 #check that x is ordered
   xdup<-sort(x)
   if(all.equal(x,xdup) !=TRUE {
 warning("x is not ordered. Result may not be meaningful.")
   }
   out<-rep(NA,length(x))
   for(i in 2:length(x)){
   out[i]<-difftime(x[i],x[i-1],units="secs")
   }
   out
}

#load raw burstiness function
getBurstiness <- function(x) {
 (sd(x,na.rm=TRUE) – mean(x,na.rm=TRUE)) / (sd(x,na.rm=TRUE) + mean(x, na.rm=TRUE))
}

#load function for simulating data with N messages
#compute: m = mean, s = SD, B = burstiness
```

```
sim<-function(x,N) {
 n<-sample(x,N)
 n<-n[order(n)]
 tau<-getTimeIntervals(n)
 data.table(N,m=mean(tau,na.rm=TRUE),s=sd(tau,na.rm=TRUE),B=getBurstiness(tau))
}

### Get complete set of times at which emails were sent (from all groups) ###

Vars <- EmailData[,c("group","T1")]
Vars<-Vars[order(Vars$T1),]
t<-Vars$T1

### Create null model for teams with N = {min:max} emails ###

#First, get list of each location's "total emails"; then get unique list of totals. This = the set of N
#load group data with tally of total emails (variable = "TotalEmails")
EmailDataV2$Count<-1
GroupEmailTotals<-aggregate(Count~group,data=EmailDataV2, FUN= "sum")
GroupTimeDiffStats=merge(GroupTimeDiffStats,GroupEmailTotals,by="group")
EmailTotals<- GroupEmailTotals [,c("Count")]
EmailTotals<-unique(EmailTotals)

#Second, for each N in EmailTotals, do a number of r repetitions (samples, taken from the entire set of emails across all groups)

set.seed(02138)
r<-1000
list<- EmailTotals[1:length(EmailTotals)]
final<-foreach(i=list, .combine=rbind) %do% {
 out<-data.table()
 for(j in 1:r) {
  out<-rbindlist(list(out,sim(t,i)))
  print(i)
 }
 out
}

BurstinessNull<-final

### Compute BZ for each group ###
GroupTimeDiffStats$BZ<-NA
for(i in 1:nrow(GroupTimeDiffStats) ) {
GroupTimeDiffStats$BZ[i]<-( GroupTimeDiffStats$RawBurstiness[i] - mean(-BurstinessNull$B[BurstinessNull$N == GroupTimeDiffStats$Count[i]]) ) / sd(BurstinessNull$B[BurstinessNull$N == GroupTimeDiffStats$Count[i]])
}
###############################
### RCM AND OLS ANALYSES ###
###############################

# VARIABLE CODE BOOK #

### Group indicator = group

### Group Performance ###
```

```
# Monthly Sales (log) = Sales

### Resources ###
# Functional Diversity (group mean centered) = FnDiv
# Group Size (group mean centered) = GrpSz

### Coordinated Attention ###
# Email Burstiness (standardized) = BZ

### Controls ###
# Age Diversity = AgeSD
# Sex Composition = PercF
# Organizational Tenure (group mean centered) = OrgTen
# Experience Working Together (group mean centered) = ExpTog
# Average Salary (group mean centered) = AvgSalary
# Prior Performance (log) = PastPerf
# Rate of Members Gained = MembGnd
# Rate of Members Lost = MembLst
# Ability: Group Rating = GrpRtg
# Effort: Total Amount of Email Communication = EmailAmt
# Leadership: Regional Manager = Mgr
# Market Factor: Quarter =Qtr
# Market Factor: FDIC Deposits (log) = FDIC
# Market Factor: Type of Location = Type

### LOAD PACKAGES ###

library(lme4)
library(stats)
library(DescTools)

### ANALYSES ###

#Table 3, Model 1: Random-intercepts
#Specify Model
Model1<- lmer(Sales ~ (1 | group),data = data, REML = F)
#Calculate Pseudo R2 for Table 3, Model 1
#Create y-hat array using the product of the model matrix (x-variable values from data) X fixed-effects coefficients (the coefficients in the model)
yhatM1 = model.matrix(Model1) %*% fixef(Model1)
#Calculate pseudo-r-squared as correlation between yhatm1 and the y-variable from dataset
cor(yhatM1,data$Sales) ^2 #PseudoR2

# Table 3, Model 2: Random-intercepts, controls
#Specify Model
Model2<- lmer(Sales ~ AgeSD + PercF + OrgTen + ExpTog + AvgSal + PastPerf + MembGnd + MembLst + GrpRat + EmailAmt + Mgr + Qtr + FDIC + Type + FnDiv + GrpSz + (1 | group),data = data, REML = F)

#Calculate Pseudo R2 for Model 2
yhatM2 = model.matrix(Model2) %*% fixef(Model2)
cor(yhatM2,data$Sales) ^2 #PseudoR2

#Table 3, Model 3: Random-intercepts, random-slopes, and controls
#Specify Model
```

```
Model3<- lmer(Sales ~ AgeSD + PercF + OrgTen + ExpTog + AvgSal + PastPerf + MembGnd + MembLst + GrpRat + EmailAmt + Mgr + Qtr + FDIC + Type + FnDiv + GrpSz + (1 + FnDiv + GrpSz | group),data = data, REML = F)

#Calculate Pseudo R2 for Model 3
yhatM3 = model.matrix(Model3) %*% fixef(Model3)
cor(yhatM3,data$Sales) ^2 #PseudoR2

#Compare Model 3 to Model 2
anova(Model3,Model2)

#Quantify Heterogeneity in Slopes – T-tests with Bonferroni Correction
tcrit<-qt(1-(.05/(nrow(RandEff))),df=(nrow(RandEff)-1)) # determine critical t value with correction

#Functional Diversity Slope
RandEff<-(coef(Model3$group[,c("FnDiv","GrpSz")]) # extract group-specific slopes
sebeta1<-(sd(RandEff$FnDiv)/sqrt(nrow(RandEff))) # determine standard error of group-specific slopes
b1test <- ((mean(RandEff$FnDiv) – RandEff$FnDiv)/sebeta1) # one-sample t-tests
# compare t values to the critical value for count of group-specific slopes that differ significantly from the mean
table(b1test > tcrit)

#Group Size Slope
RandEff<-(coef(Model3$group[,c("FnDiv","GrpSz")])
sebeta1<-(sd(RandEff$FnDiv)/sqrt(nrow(RandEff)))
b1test <- ((mean(RandEff$FnDiv) – RandEff$FnDiv)/sebeta1)
table(b1test > tcrit)

#Score the latent Resource-use Ability (RsUsAb)
#z-scores for each slope
RandEff$z_FnDiv <- (RandEff$FnDiv-mean(RandEff$FnDiv))/sd(RandEff$FnDiv)
RandEff$z_GrpSz<- (RandEff$GrpSz -mean(RandEff$GrpSz))/sd(RandEff$GrpSz)
#average of slope z-scores
RandEff$RsUsAb<-(RandEff$z_FnDiv + RandEff$z_GrpSz)/2
#then merge this value into the data set
RandEff$group<-rownames(RandEff)
CI<-RandEff[5:6]
data<-merge(data,CI,by="group")

# Table 4 Models (OLS) Predicting Group-Specific Resource Use Ability
#Specify Models
lm1<-lm(RsUsAb~BZ, data = data)
lm2<-lm(RsUsAb~BZ + GrpRtg + EmailAmt + Mgr + FDIC + Type + Qtr, data = data)
lm3<-lm(RsUsAb~ GrpRtg + EmailAmt + Mgr + FDIC + Type + Qtr, data = data)

#Table 3, Model 4: Random-intercepts, random-slopes, controls, and predictors of random slopes
#Specify Model
Model3<- lmer(Sales ~ AgeSD + PercF + OrgTen + ExpTog + AvgSal + PastPerf + MembGnd + MembLst + GrpRat + EmailAmt + Mgr + Qtr + FDIC + Type + FnDiv + GrpSz + FnDiv*BZ + GrpSz*BZ + (1 + FnDiv + GrpSz | group),data = data, REML = F)

#Calculate Pseudo R2 for Model 4
yhatM4 = model.matrix(Model4) %*% fixef(Model4)
cor(yhatM4,data$Sales) ^2 #PseudoR2
```