A Structured Approach to Forming Creative Teams in New Product Development
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Creativity is strongly influenced by the way individuals are organized. One of the most difficult and important challenges when managing innovation is to identify the individuals within an organization who must work closely with each other in order to maximize the generation of creative ideas. This paper introduces a structured approach to guide managers of new product development organizations on their decisions to form a temporary team (or task force) from which creative solutions would be demanded. Our approach exploits the notion of creative interactions, which recognizes that people trigger the generation of creative ideas when interacting with each other for task-related matters. Our approach is structured in three basic steps: (1) capturing the current organizational structure; (2) measuring creative dyadic interactions; and (3) forming clusters of creatives. The intent of our approach is to identify groups of individuals within the organization who have a history of triggering the generation of creative ideas when interacting with each other. The basic premise underlying this approach is that the occurrence of past creative interactions predicts the occurrence of creative interactions in future design efforts. We design an experiment to test this hypothesis with participants in an Executive MBA program. We then illustrate our approach by implementing it in the new product development department of a European software firm, and we discuss the organizational implications of implementing this approach.

Keywords: creativity; design teams; new product development organizations; clustering algorithms
1 Introduction

Who shall we invite to our next series of brainstorming sessions? Who should be assigned to the next task force responsible for generating creative solutions for ...? These questions are commonly faced by innovation managers, who typically address them on an ad hoc basis rather than taking into account how the organization actually works when developing new products and services. This paper introduces a structured approach to guide managers in new product development as they address such questions. We first examine, in a quasi-natural experiment, the underlying assumption on which our approach is based, and we then illustrate the implementation of our approach in a real organizational setting.

One of the most important and difficult challenges that innovation managers face when assigning people to a team (or task force) is to evaluate the team’s potential to achieve high levels of creativity. The challenge of “how to make the team” for high performance in research and development (R&D) organizations has been studied in the organizational literature (Reagans and Zuckerman 2001, Reagans et al. 2004). This stream of work has found that managers often use demographic information such as gender, educational background, and tenure in the firm when assigning people to project teams in R&D organizations. The rationale for these choices assumes that demographic data is a good indicator of the resources and knowledge that individuals would bring to the team. However, the effectiveness of this approach is limited because demographic data need not be correlated with how individuals communicate when dealing with their technical interdependencies with other colleagues in the organization (Reagans et al. 2004).

The creativity literature has addressed the challenge of organizing for creativity in various ways (Amabile 1996, Sternberg 1999). Here we use the most widely accepted notion of creativity: the ability to produce something that is both novel and useful (Amabile 1996, Csikszentmihalyi 1996). The work of Amabile (1996) pays particular attention to the role of intrinsic motivation to work on the task as a significant determinant of creativity. As a result, such motivation is considered to be an important criterion when deciding who should be assigned to a creative team (Amabile 1997). Previous research on creativity has also emphasized the role of knowledge diversity in generating novel and useful ideas (Simonton 1988, Hargadon and Sutton 1997, Burt 2004, Fleming et al. 2007). Thus, grouping people with diverse backgrounds and experiences is likely to increase the group’s creativity (Sutton and Hargadon 1996, Choi and Thompson 2005, Kavadias and Sommer 2009). Although experimental and empirical research has provided evidence that support these findings, what
is often overlooked is that individuals in established organizations are likely to be involved in many noncreative tasks that require more coordination than innovation does (Allen 1977, Sosa et al. 2004). Even so, such task-related interactions are likely to influence the capability of individuals to generate creative ideas (Hargadon and Bechky 2006). We contribute to this stream of work by suggesting an alternative approach to forming design teams that are to maximizing creative output.

“A product development organization is the scheme by which individual designers and developers are linked together into groups” (Ulrich and Eppinger 2004, p. 23). Typically, product development organizations group their individuals based on functional areas or specific projects (or a combination of both). Such formal organizational structures shape not only the communication patterns among individuals within them but also the outcomes for individuals from their interactions with others (Allen 1977, Sosa et al. 2004). In exploring how product development actors interact with each other to address their task interdependencies, previous research has studied the relationship between the communication patterns of developers in the organization and the structure of either the products they develop or the process they use to develop those products (McCord and Eppinger 1993, Morelli et al. 1995, Sosa et al. 2003, Sosa 2008). Using a simulation-based approach, Olson et al. (2009) study the interplay between the structure of a complex design problem and the design of a team responsible for solving it in order to develop guidelines to manage task complexity while searching for innovative solutions. A game-theoretical approach (Takai 2010) models dyadic collaboration of engineers in design projects and finds that common project-related knowledge and diversity of background are important drivers of team performance. We contribute to this stream of work by looking at dyadic interactions not only as coordination mechanisms but also as key triggers for the generation of creative ideas.

Our approach relies on measuring creative interactions—in other words, capturing the extent to which individuals trigger the generation of creative ideas on other individuals with whom they have task-related interactions in their current organizational form. We then use such a dyadic information as the main input to our clustering analysis, which yields suggestions on how to group individuals who are likely to generate creative ideas when they interact with each other. Toward that end, we develop clustering techniques to form creative teams by bringing people with positive creative interactions together and by excluding those with negative interactions from the proposed creative teams (or clusters of creatives).

A fundamental hypothesis underlying our approach is that pairs of actors who have had positive creative interactions in the past will contribute positively to creative performance.
if put together in a team. Here we test this hypothesis using an experimental approach with a set of executive participants in an international MBA program. We then use the experimental results to refine our structured approach when applying it to generate alternative organizational configurations that foster creativity in the new product development department of an actual company.

2 Our Structured Approach

We have developed a structured approach to forming creative teams. This approach is summarized in three steps as follows (see Figure 1).

![Figure 1. Structured approach to forming creative teams](image)

**Step 1: Capture Current Organizational Structure.** First, we suggest capturing the formal and informal structure of the organization by documenting how developers are assigned to organizational groups and how often they interact to address their task-related interdependencies. This step is important not only for documenting the set of dyads that will provide information about the creative potential of individuals in the organization (see Step 2) but also for constructing a baseline against which creativity potential improvements can be assessed (at the completion of Step 3). By surveying all development actors in the organization, we document their actual task-related interactions in a square (person-to-person) *actual communication matrix* \( \mathbf{A} \). The columns of the matrix are labeled with the “source” of task-related information and the rows are labeled with the “recipients” of that information. For example, cell \( a_{ij} \) indicates that actor \( i \) “goes to” actor \( j \) to request task-related information. In the matrix, actors who belong to the same organizational group are sequenced together so that we may easily distinguish interactions within groups from those across groups. This approach is similar to that used by previous works in product development that

**Step 2: Measure Creative Dyadic Interactions.** In product development organizations, individuals seek other colleagues to search for task-related information in order to address their task interdependencies. The recipient is the actor who “goes to the source to discuss task-related matters” during the product development effort. Creative interactions are those in which the recipient is likely to generate novel and useful ideas after receiving technical information from the source (Sosa 2010). Hence, for each identified dyadic interaction we document the recipient’s ability to easily generate creative ideas after interacting with the source. We capture such information in a creative interaction matrix \( D \), which uses the same sequence as the actual communication matrix \( A \) described in Step 1. Relying on the recipient in the dyad to assess the potential novelty and usefulness of her ideas is consistent with Simonton (1988), who suggests that the creator evaluates her creations before presenting them to the community for further scrutiny. This is also in line with Csikszentmihalyi (1996), who acknowledges that a person seeking to make a creative contribution must learn the criteria of selection and the preferences of her audience, which ultimately determine the contributions novelty and usefulness. This is especially pertinent to product development organizations, where individuals have a common understanding of the knowledge domain in which ideas would be valuable and understand well the criteria that would categorize an idea as novel and useful.

**Step 3: Form Clusters of Creatives.** We formulate the challenge of clustering individuals with positive creative interactions (while excluding those with negative creative interactions) as an optimization problem that maximizes the creative potential of the organization. (Details of our clustering formulation are discussed in section 4.) Our formulation results in clusters of individuals who report generating creative ideas after interacting with each other for task-related matters. We document the resulting new organizational form in a clustered creativity matrix \( C \). This alternative organizational arrangement helps identify the groups of people that, if brought together for a temporary assignment such as a task force engagement or brainstorming session, are likely to generate potentially creative ideas.

**Our Working Hypothesis.** The three-step approach displayed in Figure 1 assumes that grouping people with a history of facilitating the generation of creative ideas in task-related interactions will likely lead to generation of creative ideas in future assignments that require
creative outcomes. This assumption is consistent with recent literature on team familiarity that indicates familiarity among team members (due to working together on previous projects) is associated with better project performance. In a study of fluid teams in a large software development firm, Huckman et al. (2009) find that teams whose members worked together on previous projects were likely to perform better than teams whose members were not previously familiar with each other. Such empirical evidence is in line with simulation-based studies showing a positive relationship between team familiarity and team performance (Singh et al. 2009).

A positive relationship between team familiarity and team performance is also consistent with the literature on creativity that suggests organizational factors that intrinsically motivate designers are likely to have a positive effect on individual creativity (Amabile 1996). Also in the organizational domain, the literature on social networks has studied the relationship between past collaborations and creativity. For instance, Singh and Fleming (2010) find that inventors who work in teams, rather than alone, are more likely to create breakthroughs and less likely to invent particularly poor outcomes; and Obstfeld (2005) finds that engineers (in an automobile firm) who are likely to be involved in innovative initiatives are the ones who foster a collaborative environment around them.

Although we take into account past interactions to form creative teams, we do not suggest that repeat interactions necessarily foster creativity. Indeed, it has been recently argued that a team that has been together for several engagements is less likely to be creative because the team’s inertia developed in earlier projects is expected to interfere with its creative processes (Skilton and Dooley 2010). Our argument focuses on the quality of past interactions (rather than their frequency) and our approach offers the possibility of reconfiguring previously formed organizational groups to improve the creativity potential of the organization. In other words, we argue that the pairing with a colleague with whom one has previously had positive creative working experiences is an important motivational and collaborative factor that is likely to have a positive impact on individual and group creativity. Although this argument is grounded in previous work, it is crucial that we test it empirically because our structured approach relies on the validity of such a conjecture. Specifically, we formulate the following working hypothesis.

**Positive creative interactions in the past predict creative performance in future design efforts.**
3 The Experiment

We use an experimental approach to test our working hypothesis (Linsey et al. 2010). This required a setting in which a set of participants could perform a controlled design exercise and also in which we could capture the communication patterns among participants before the design exercise. We took advantage of the natural setting in an executive master’s of business administration (EMBA) program to carry out our experiment.

3.1 Participants and Design

The experiment was completed by all 34 participants (25 males, 9 females) enrolled in an EMBA program jointly offered by Tsinghua University and INSEAD (http://tsinghua.insead.edu.sg/). The program is called TIEMBA, and participants belonged to the graduating class of 2010. (The average age of the participants was 38 years, and their average work experience was 13 years.) The TIEMBA program lasts 1.5 years (starting in June and finishing in December) over 11 two-week modules approximately every six weeks. Modules take place in four different locations: Beijing (China), Singapore, Abu Dhabi (United Arab Emirates), and Fontainebleau (France). The experiment took place in the 9th module of the program—that is, after participants had completed Modules 1–8 together. This provided an ideal setting because participants had the opportunity to interact on academic-related matters for more than 11 months prior to the experiment. The experiment took place in the month of May as part of a course taught in Fontainebleau. Figure 2 shows, in bold-frame boxes, the experiment’s three milestones within the context of the TIEMBA program: the first survey, the team design exercise, and the second survey. These three milestones will be detailed next, after which we describe the measures and statistical analysis carried out to test our hypothesis.
3.2 Survey 1: Capturing Past Creative Interactions

The first survey was designed to capture the communication patterns of the 34 participants based on their involvement during academic-related tasks in the first eight modules. A short presentation to all participants at the beginning of the module was made to introduce the objective of the survey. At that point, it was important to emphasize both the research nature of the experiment and its complete disconnection with the grading of any of the program’s courses. Each participant was given a sealed envelope containing the survey instrument and was asked to fill it out individually and confidentially. Participation in the experiment was not compulsory, yet we obtained a 100% response rate on this survey.

The survey was structured in two sections. The first section included a couple of short questions that could be relevant to the outcome of the design exercise:

- What is your proficiency in French? [Not proficient at all / Just enough to have a short French conversation on the street / Fluent in French]¹
- Have you worked on new product development before? [Yes / No]

The second section of the survey was a typical social network instrument (Wasserman and Faust 1994). The survey displayed a roster of the 34 participants followed by three questions concerning the respondent’s interaction with each classmate. The three questions

¹ The answer to this question was relevant because the design exercise would involve talking to “customers” in a French marketplace.
measure (from the respondent’s viewpoint) past dyadic communication frequency, closeness, and ease of generating creative ideas.

- **Communication frequency** was measured with the following question. *Since the TIEMBA programme started (and before this Module 9 started), have you worked with this [classmate] in any group assignment (either in class or outside classes)?* [0 = No; 1 = Yes, a few times; 2 = Yes, many times]

- **Closeness** was measured with the following question (cf. Reagans and McEvily 2003, Sosa 2010). *How close is your academic relationship with this [classmate]?* [4 = Very close, this person is among my favorite classmates to work with; 3 = Close, we enjoy working together in TIEMBA assignments and exercises; 2 = Less than close; 1 = Distant, we interact only when strictly necessary]

- **Ease of generating creative ideas** was measured with the following question (cf. Tortoriello 2005, Sosa 2010). *Based on your interactions with this [classmate] in TIEMBA assignments or exercises (either in class or outside the classroom), please indicate your level of agreement with the following statement:*

  “When I interact with this person, it is easy for me to generate NOVEL creative solutions and/or ideas. These novel ideas can be specific to solutions of TIEMBA assignments or to the way we do things (within TIEMBA academic activities).” [7-point scale: Strongly disagree; Disagree; Marginally disagree; Neither agree nor disagree; Marginally agree; Agree; Strongly agree]

Consistent with Amabile (1996), the question that measures the respondent’s ease of generating creative ideas does not incorporate an explicit definition of creativity. However, the question captures both the novelty and usefulness dimensions of creativity so that the respondent can make an accurate assessment of the ease of generating potentially creative ideas after interacting with each contact for academic-related matters.

Each participant filling out this survey was asked the three “network” questions just described for each of the other 33 participants on the roster. Although the 34 participants knew each other because they had been taking classes together in eight modules of the program prior to the design exercise, not every person had worked with every other in class assignments and/or class exercises. Hence, respondents could report “null” past interactions with some of their classmates. A respondent could answer the question about closeness for all other 33 participants, but the question about the ease of generating creative ideas was applicable only for classmates with nonzero communication frequency. (Nonetheless, some
respondents reported a nonzero value for ease of generating creative ideas in cases of null communication frequency during TIEMBA assignments; this may occur because participants interacted with each other even if they did not work together on TIEMBA assignments.)

Figure 3 shows a creative interaction matrix whose cell \((i, j)\) captures actor \(i\)'s ease of generating creative ideas after interacting with actor \(j\) during academic assignments before Module 9. This matrix is an instance of the creative interaction matrix described in Step 2 of our structured approach.

![Creative Interaction Matrix](image)

**Figure 3.** Past creative interaction matrix of the experiment

### 3.3 Team Design Exercise

The design exercise was part of a two-day course on Innovation Management taught by the first author to all 34 TIEMBA participants during the 9th module of the program. The first day of the course introduced basic design principles for address the three main challenges of an innovation project: understanding customer needs, generating product concepts, and prototyping and testing final solutions (Bhavani and Sosa 2008).

The second day of the course was dedicated to designing an “artifact” (i.e., a bag) to facilitate grocery shopping in a typical French open-air market (Ulrich 2004). There were three types of design activities associated with this exercise: (i) assessment of customer needs, which included visiting the open-air market in Fontainebleau; (ii) ideation to generate alternative solutions; and (iii) building a final prototype of the product concept.

The class was split into eight design teams, which would carry out the design exercise in parallel. The eight teams were formed in a two-step process. First, 8 of the 11 participants who reported being proficient in French were randomly selected, and each was assigned to
one of the eight teams. This guaranteed that every team had at least one person proficient in French. Second, the rest of the participants were randomly assigned to one of the eight teams. We formed six teams with four participants and two teams with five participants.

All teams were provided with the same set of materials to build their prototypes, and each team had a dedicated, closed cubicle to complete their design exercise. Most of the interactions during the exercise took place within the team. Interactions external to the team were limited to short interactions with random “customers” in the marketplace and with the instructor (for clarification on the scope of the exercise). Participants did not interact with members of other teams during the design exercise. At the end of the day, a “shopping bag exhibition” was organized to evaluate the prototypes produced by each team. Each team was given the opportunity to present their product concept and prototype (with a suggested retail price) to their classmates, and participants could vote for their two favorite designs (excluding their own).

3.4 Survey 2: Capturing Creative Interactions During the Team Design Exercise

At the end of the exercise, individuals were asked to fill out a short follow-up survey to rate the level of creativity of their interactions with other team members during the exercise. Responses were completely confidential. In addition, participants were assured that their responses were processed after course grades were submitted, assuring that responses would not influence their course performance in any way.

This second survey was structured in two sections. The first section captured various dimensions of team dynamics; the second section focused on interactions of the respondent with other team members during the exercise.

To capture team dynamics, respondents were asked to indicate their level of agreement with each of the following statements (Lovejoy 2000).

- *My thoughts and comments were respected and considered by my teammates.*
- *Our team worked well together.*
- *Each member of our team contributed their fair share to the joint effort.*
- *Our team was able to make high-quality decisions.*

To capture the level of creativity of the respondent’s interactions with other team members, respondents were asked to indicate their level of agreement with the following statement:
Interacting with (or listening to) [full name of team member] during the shopping bag exercise helped me to generate novel and useful ideas that contributed to the development of our product (or the way we did things).

As in Survey 1, levels of agreement with all statements were measured on a 7-point Likert scale ranging from “strongly disagree” to “strongly agree”. Figure 4 shows the creative interaction matrix reflecting respondents’ answers to the last question of Survey 2. This matrix follows the same sequencing as the one shown in Figure 3, but it is significantly less dense because we measure only the creative interactions of dyads that were active during the design exercise.

![Figure 4. Creative interaction matrix (during the design exercise)](image)

### 3.5 Team-Level Analysis

Even though we have only seven valid observations at the team level,² we find empirical evidence that teams with more positive creative interactions during the design exercise (as measured by Survey 2) garnered more votes during the “shopping bag exhibition”. The correlation between the average ratings for team dynamics and the fraction of votes received by a team is 0.572 ($p < .180$). More telling is that the correlation between a team’s “average creative interaction” during the design exercise and the fraction of votes received by that team was both positive and significant (0.682, $p < .091$). Figure 5 shows an ordinary least-squares (OLS) regression estimate of the fraction of votes received by the final product of

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² For this analysis, we excluded the data from one team that priced their product outside the range that was considered “fair” by the audience making it an outlier data point.
each team (a “simulated market share”) as a linear function of the average of creative interaction as reported by the team’s members. Consistent with the correlation analysis, the regression has a positive and significant coefficient for the effect of average creative interaction on simulated market share (6.736, \( p < .091 \)), which provides initial empirical support for our hypothesis that teams that clustered past positive creative interactions are more likely to produce potentially novel and useful outcomes.

![Graph showing team outcome as a function of team average creative interaction](image)

**Figure 5.** Team outcome as a function of team average creative interaction

### 3.6 Dyadic Measures
Because we have only seven valid observations at the team level, the team-level results in the previous section are merely suggestive of empirical support for our hypothesis. A more rigorous statistical inference from our experimental data requires that we carry out our analysis at the dyadic level. Hence, we use the dyads that were active during the design exercise as our main unit of analysis: we focus on predicting the creative performance (as measured in Survey 2) of each dyad during the design exercise.

In general, a dyad is formed by an actor receiving information (the recipient) and an actor providing information (the source). As a result, our sample could include as many as 112 observations corresponding to 72 directed dyads from the six four-member teams and 40 directed dyads from the two five-member teams. We refer to dyads as “directed” because we consider each dyad from the recipient’s viewpoint.
Next we shall describe the variables used in our statistical analysis. In the analysis, we estimate a regression model that predicts the ease of generating creative ideas during the design exercise as a function of past creative interactions—while controlling for several factors that could also affect the creative process during the design exercise.

**Dependent Variable.** *Ease of generating creative ideas from interactions with other team members during the design exercise.* Our dependent variable captures how other team members trigger the generation of creative ideas by the recipient, and it is measured using the last question of Survey 2 (and shown in Figure 4). This variable assesses how good the source (i.e., a team member) was at triggering the recipient’s creative ideas during the design exercise.

**Predictor Variables.** The key predictor variables in our analysis are a function of the level of creativity associated with past interactions among the participants prior to the design exercise. Using answers to the last (“ease of generating”) question of Survey 1 (and shown in Figure 3), we build two alternative measures of past creative interactions. The only difference between these two alternative measures is who assesses the ability of the source $j$ (i.e., a recipient’s teammate during the design exercise) to trigger the generation of creative ideas by the recipient $i$.

- **Creative interaction assessed by the recipient.** This dyadic measure uses a 7-point Likert scale to capture (from the recipient’s viewpoint) how good the source was at triggering creative ideas by the recipient in the past (prior to the beginning of Module 9), as assessed by the last question of Survey 1.

- **Creative interaction assessed by the class.** This dyadic variable measures the average ratings received by the source (actor $j$) from all the classmates who reported past interactions with $j$ but excluding the focal respondent (actor $i$). Hence, this variable captures how good the source was, on average, at triggering creative ideas by all other classmates who interacted with him in the past (i.e., prior to the start of Module 9).

One objective of the statistical analysis described in the next section is to test which of these alternative independent variables is a better predictor of our dependent variable.

**Control Variables.** There are several control variables that must be included in our analysis to ensure that the effects of the predictor variables are distinguishable from the effects of potentially confounding variables that could also explain variation in the dependent variable. Just as for the dependent and predictor variables, we defined the following control variables for each dyad that was active during the design exercise.
• **Same demographics.** Because similarities in demographics can facilitate knowledge sharing and the generation of creative ideas, we include an indicator variable that measures whether or not the source and recipient of each dyad are of the **same gender** (1 if interacting actors of same gender and 0 otherwise). Similarly, we include an indicator variable to capture whether or not the source and the recipient are from the **same nationality**.

• **New product development experience.** Because the experience of either the source or the recipient in new product development may help to generate creative ideas, we include two indicator variables that capture whether the source and/or recipient worked in new product development before joining the TIEMBA program.

• **Past communication frequency.** Communication frequency is an indicator of the strength of a dyadic relationship. Since strong dyadic relationships are associated with ease of knowledge transfer, it is important to control for the communication frequency of past interactions between source and recipient (Reagans and McEvily 2003, Sosa 2010). Including this variable is also important for ruling out the possibility that creative interactions are predicted by lack of prior interaction with the source (Skilton and Dooley 2010). We measure past communication frequency for each active dyad based on the answer of the dyad’s recipient to the “communication frequency” question of Survey 1 corresponding to the dyad’s source.

• **Dyadic closeness.** Close dyadic relationships are associated with pairs of people who intrinsically enjoy working with each other, which in turn is positively correlated with the generation of creative ideas (Sosa 2010). It is therefore important to control for the emotional attraction between the source and the recipient. We measure dyadic closeness based on the response of a dyad’s recipient to the “closeness” question of Survey 1 corresponding to the dyad’s source.

• **Recipient’s creativity potential.** In order to control for a recipient’s general propensity to rate higher (or lower) the ease of generating creative ideas after interacting with others, we include the average creative interaction rating provided by the recipient $i$ to all other classmates that she interacted with in the past but excluding actor $j$. Past creative interactions ratings provided by the recipient were captured by the last question of Survey 1. This variable controls for the intrinsic role of the recipient in generating creative ideas.
• **Team dynamics.** Because team dynamics during the design exercise could influence the outcome of dyadic interactions within the team, we include a team-level variable that controls for perceived team dynamics as reported by all members of a given team. In order to measure this, we calculate the average rating of the first four questions of Survey 2 across all members of each team.

• **Team-level fixed effects.** In order to control for any unobserved characteristic of design teams (e.g., their previous experience with grocery shopping) that could potentially influence the team’s creative output, our regression models include team-level fixed effects in the standard way of defining an indicator variable for every team in our sample (Wooldridge 2002). These indicator variables will be 0 for all teams except the one to which the focal dyad belongs.

Table 1 presents descriptive statistics and pairwise correlations of the variables included in our statistical analysis.
Table 1. Descriptive Statistics and Pairwise Correlations

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<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<td>0.50</td>
<td>0.00</td>
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<td>4. NPD experience of recipient</td>
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<td>5. NPD experience of source</td>
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<td>4.93</td>
<td>0.47</td>
<td>0.08</td>
<td>0.10</td>
<td>0.14</td>
<td>0.20</td>
<td>-0.11</td>
<td>0.15</td>
<td>0.30</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Team dynamics</td>
<td>106</td>
<td>5.88</td>
<td>0.51</td>
<td>0.26</td>
<td>-0.04</td>
<td>-0.09</td>
<td>0.34</td>
<td>0.53</td>
<td>-0.17</td>
<td>-0.11</td>
<td>-0.19</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>10. Creative interaction assessed by recipient</td>
<td>91</td>
<td>5.15</td>
<td>1.27</td>
<td>0.26</td>
<td>0.14</td>
<td>-0.01</td>
<td>0.17</td>
<td>-0.09</td>
<td>0.18</td>
<td>0.66</td>
<td>0.34</td>
<td>-0.14</td>
<td>1.00</td>
</tr>
<tr>
<td>11. Creative interaction assessed by the class</td>
<td>106</td>
<td>4.92</td>
<td>0.55</td>
<td>0.31</td>
<td>0.48</td>
<td>-0.33</td>
<td>0.17</td>
<td>-0.03</td>
<td>0.07</td>
<td>0.42</td>
<td>-0.04</td>
<td>0.03</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Note: Correlation coefficients greater than |0.26| are significant at the .01 level

3.7 Dyadic Analysis

Our dependent variable is the ease of generating creative ideas after interacting with other team members during the design exercise. For the test of our working hypothesis we have a maximum of 95 observations: two participants could not fill out Survey 2, which reduced the original potential set of 112 observations to 106; and dyadic closeness was not defined for 11 dyads with null communication frequency, reducing our number of observations with complete data to 95. (Results with 106 observations but excluding dyadic closeness were consistent with those reported here.) The dependent variable is ordered and discrete, so an ordered probit regression model is used as the main statistical approach; these results are reported in Table 2. In an ordered probit regression, an underlying probability score is estimated as a linear function of a set of independent variables and a set of cutoff points.
Thus, the probability of observing outcome \(i\) corresponds to the probability that the estimated linear function (plus random error) is within the range of the cutoff points estimated for the outcome (Wooldridge 2002):

\[
P(\text{outcome}_j = i) = P(\kappa_{i-1} < \beta_1 x_{1j} + \beta_2 x_{2j} + \cdots + \beta_k x_{kj} + u_j \leq \kappa_i),
\]

where \(u_j\) is assumed to be normally distributed. Using maximum likelihood, we can estimate the coefficients \(\beta_1, \beta_2, \ldots, \beta_k\) along with the cutoff points \(\kappa_1, \kappa_2, \ldots, \kappa_{j-1}\), where \(I\) is the number of possible outcomes (in our case, \(I = 7\) because the dependent variable is measured on a 7-point scale) and where \(\kappa_0\) is taken to be \(-\infty\) and \(\kappa_I\) to be \(+\infty\). For instance, if the outcome of the regression function (for a given set of values of the independent variables) is less than or equal to \(\kappa_1\) then the predicted value of this regression corresponds to the recipient “strongly disagreeing” that it is easy to generate creative ideas after interacting with the source; likewise, if the regression outcome is greater than \(\kappa_6\) then our model predicts that the recipient “strongly agrees” that it is easy to generate creative ideas after interacting with the source. As for the coefficients shown in Table 2, a positive coefficient \(\beta_k\) indicates that an increment in predictor \(x_k\) shifts the underlying probability distribution of the dependent variable to a higher level. Hence, the sign and statistical significance of the coefficients of our ordered probit regressions can be interpreted similarly to those in OLS regressions. Ordered logit regressions yield similar results.

Because dyads within the same team are unlikely to be independent observations, we estimate robust standard errors clustered by design teams (Wooldridge 2002). Calculating clustered standard errors in this way allows for nonindependent observations within the cluster (i.e., design teams) while assuming that observations are independent across clusters (Williams 2000, Baum 2006). This is a reasonable assumption when one considers the setup of our design exercise.

Table 2 shows the coefficients of the ordered probit regression models predicting ease of generating creative ideas during the design exercise. Model 1 includes the set of control variables. As expected, both past communication frequency and dyadic closeness are positive and significantly correlated with creative idea generation. Moreover, positive team dynamics were positively associated with creative idea generation (0.569, \(p < .097\)).\(^3\) Model 2 includes one of our predictor variables (past creative interaction assessed by the recipient); this model

\(^3\) Although the inclusion of team dynamics in the presence of team-level fixed effects does not affect the coefficient estimates of our dyadic variables, we still report the team dynamic coefficient to test for the expected positive link between team dynamics and ease of creative idea generation.
excludes 15 observations in which the recipient had not reported past interactions with the
corresponding team member. Model 2 includes a positive (albeit not significantly different
from zero) coefficient for recipient’s past creative interaction (0.163, \(p < .422\)), which
indicates that past creative interactions (as reported by the recipient) do not predict positive
creative interactions during the design exercise. This would seem to indicate, at first, that the
empirical data does not support our working hypothesis.

### Table 2

**Ordered Probit Coefficients Predicting Positive Creative Interactions During the Design Exercise**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Same gender</td>
<td>−.314</td>
<td>−.286</td>
<td>−.529</td>
<td>−.611</td>
<td>−.306</td>
</tr>
<tr>
<td>Same nationality</td>
<td>−.555</td>
<td>−.110</td>
<td>−.142</td>
<td>−.574</td>
<td>−.177</td>
</tr>
<tr>
<td>NPD experience of recipient</td>
<td>−.581</td>
<td>−.902**</td>
<td>−.649</td>
<td>−1.047**</td>
<td>.949***</td>
</tr>
<tr>
<td>NPD experience of source</td>
<td>−.154</td>
<td>−.176</td>
<td>.328</td>
<td>−.378</td>
<td>.204</td>
</tr>
<tr>
<td>Past communication frequency</td>
<td>−.376*</td>
<td>.157</td>
<td>.463***</td>
<td>.217</td>
<td>.223</td>
</tr>
<tr>
<td>Dyadic Closeness</td>
<td>.451*</td>
<td>.314</td>
<td>.236</td>
<td>.123</td>
<td>.119</td>
</tr>
<tr>
<td>Recipient’s creativity</td>
<td>.054</td>
<td>.180</td>
<td>.211</td>
<td>.487</td>
<td>.195</td>
</tr>
<tr>
<td>Team dynamics</td>
<td>.569*</td>
<td>.375</td>
<td>1.054***</td>
<td>.671*</td>
<td>.521*</td>
</tr>
<tr>
<td>Creative interaction</td>
<td>.163</td>
<td>.021</td>
<td>.289***</td>
<td>.411</td>
<td></td>
</tr>
<tr>
<td>Log pseudolikelihood</td>
<td>−102.77</td>
<td>−92.49</td>
<td>−100.26</td>
<td>−88.52</td>
<td>−98.50</td>
</tr>
<tr>
<td>Pseudo-(R^2)</td>
<td>.1369</td>
<td>.1507</td>
<td>.1580</td>
<td>.1872</td>
<td>.1727</td>
</tr>
<tr>
<td>Number of observations</td>
<td>95</td>
<td>91</td>
<td>95</td>
<td>91</td>
<td>95</td>
</tr>
</tbody>
</table>

**Notes:** Models include fixed effects for each team. Robust standard errors (in parentheses) are clustered by team.

\*\(p < .10\), \**\(p < .05\), \***\(p < .01\) (two-tailed)
Model 3 includes our alternative predictor variable (creative interactions assessed by the class). This model shows a positive and significant coefficient of the predictor variable (0.775, \( p < .007 \)). This suggests that recipients who interacted with team members who were rated by other classmates as effective catalysts of creative ideas in previous modules of the program are more likely to generate creative ideas during the design exercise. Here, then, there is strong empirical support for our working hypothesis. Model 4 includes both of our predictor variables. Consistent with results under Models 2 and 3, the source’s rating as catalyst of past creative interactions is—whereas the recipient’s past creative interaction is not—a significant predictor of creative interactions in the design exercise. We also estimate an alternative version of Model 4 (not shown in Table 2) that includes an interaction effect between recipient’s creative potential and creative interaction assessed by the class to test whether the positive effect of interacting with someone who has been rated by the class as an effective creativity catalyst was magnified when paired with a recipient that had high creativity potential. The interaction effect was not significantly different from zero.

Finally, we combine our two predictor variables into a single composite variable defined as the sum of creative interaction assessed by the recipient and by the class;\(^4\) this composite predictor variable is included in Model 5. This model shows a positive and significant coefficient (0.289, \( p < .009 \)) of the composite predictor variable, which suggests that we can predict creative interactions in the design exercise by combining the recipient’s assessment of her past creative interactions with the average ratings received by the source concerning the creativity of his past interactions.\(^5\)

Our experimental results suggest that the collective wisdom of the TIEMBA class derived from their past interactions was a significant predictor of the performance of pairs of individuals working together in the design exercise. This predictive power was even more significant than that of the individuals’ previous experiences of working with each other. The result is consistent with recent organizational literature that highlights the power of “crowds” to discern complex decisions (Mannes 2009)—in our case, the power of an organization to predict the creative effectiveness of pairs of individuals embedded in design teams. It is

\(^4\) This composite creative interaction variable takes the value of creative interaction assessed by the class for the few dyads in which the recipient did not assess the ease of creative idea generation (owing to lack of past interaction with the corresponding team member).

\(^5\) We also estimated a model with another composite variable that summed the two predictor variables for dyads with positive values of creative interaction assessed by the recipient and, for other dyads (with either negative or null creative interaction assessments made by the recipient) set the composite variable equal to creative interaction assessed by the class. Consistent with Model 5, the coefficient estimate for this alternative composite variable was also positive and significant (0.242, \( p < .078 \)).
important that our experimental results provided relevant insights enabling us to refine our original structured approach to forming creative teams. In particular: because the collective assessment of the organization is a better predictor of the ease of creative idea generation in future design efforts, we need to revise the content of the creative interaction matrix (defined in Step 2 of our approach) to reflect this crucial finding. We illustrate this point next with an industry application of our approach.

4 An Industry Application

We implemented our structured approach in a software development firm. The firm, founded in the 1980s, is a public company that is traded on the German stock exchange. It is one of the world leaders for a particular type of application in the software industry, and its principal market consists of business customers. The firm’s development organization is distributed across three different locations in two neighboring European countries. During the time of data collection, the development department worked on the development of seven distinct software products. The empirical study focused on the firm’s development department (Sosa 2008, 2010).

We used two methods to collect the data: semistructured interviews and a Web survey. First we conducted semistructured interviews with the executive team of the firm, including the CEO and VP of development, and groups’ leaders to understand their portfolio of products, general organizational structure, and the nature of workloads in the organization. Then we created and distributed throughout the development organization a survey to capture individual data on product development activities and organizational interactions with other members of the development department. The survey took an average of 49 minutes to complete and was completed by 58 of the 66 people in the development department (88% response rate).

4.1 Step 1: Capture Current Organizational Structure

The development department studied was formally organized into ten groups: seven development groups (i.e., programmers); a quality control group for testing all the products; one architecting and managerial group (which made important software architecture decisions and managed the department’s resources); and one support group responsible for

6 One of these development groups was further divided into two small subgroups, but for the purpose of our analysis we consider it as a single functional group.
documentation and information systems. The quality/testing group was evenly distributed among the firm’s three locations, while the other organizational groups were almost evenly distributed between its two largest sites. We used a combination of classic sociometric techniques (Wasserman and Faust 1994, pp. 43–54) to capture the technical communication patterns both within and across organizational groups associated with the development of the seven products in the firm’s portfolio. First, each respondent was provided with a fixed roster of contacts formed by all the members of the new product development department. The full name and location of each person was clearly specified in the Web-based survey, and respondents were asked to select those they had “gone to” for interactions that significantly affected their work during 2005 (Sosa 2010).

We documented these data in an actual communication matrix (A) whose off-diagonal entries \((i, j)\) indicate whether the person in row \(i\) went to person in column \(j\) to request product-related information during the last year. Note that we sequence this matrix to reflect the organization’s structure of ten functional groups; hence, the matrix sequences together people who belong to the same organizational group. Figure 6 shows the actual technical communication patterns of the organization studied in a 58 × 58 actual communication matrix. Respondents reported 632 product-related interactions in which actor \(i\) “went to” actor \(j\) for product-related information. The result is an actual communication matrix with density of 19%.

---

**Notes:**
- Rows and columns are equally labeled with the names of the individuals that form the new product development department in our research site.
- A mark on cell \((i, j)\) indicates that the individual in row \(i\) requested task-related information to the individual in column \(j\) during the past year.
4.2 Step 2: Measure Creative Dyadic Interactions

We measure creativity (at the dyadic level) for each task-related interaction identified in Step 1. We relied on the recipient of each identified dyadic relationship to rate the ease of generating creative ideas after interacting with the source during the past year. The ease of generating creative ideas associated with each relationship was captured by asking each respondent to rate, on a 7-point Likert scale (from “strongly disagree” to “strongly agree”), their level of agreement with the following statement (Tortoriello 2005, Sosa 2010): “When I interact with [name of source contact], it is easy for me to generate NOVEL creative solutions and/or ideas. These NOVEL ideas can be either related to our products or the way we do things.” Observe that here we measured the level of creativity associated with each task-related interaction in a similar fashion as we did in Survey 1 of the experiment (see Section 3.2).

We documented the creative interaction data in a creativity interaction matrix. Figure 7 shows the creative interaction matrix of this organization, which follows the same sequencing as the actual communication matrix shown in Figure 6. Although creative interactions are documented in a seven-point scale, we may categorize these interactions more broadly as follows.

- **44 negative** creative interactions that hindered the generation of creative ideas by the recipient: those interactions that were evaluated at the three lowest levels of the 7-point scale indicating some level of difficulty of the recipient to generate potentially creative ideas after interacting with the source (7% of task-related interactions)
- **221 neutral** creative interactions that did not significantly affect the generation of creative ideas by the recipient: those interactions evaluated at the midpoint of the 7-point scale (35% of task-related interactions)
- **367 positive** creative interactions that triggered the generation of creative ideas by the recipient: those evaluated at the three highest levels of the 7-point scale indicating some level of easiness of the recipient to generate potentially creative ideas after interacting with the source (58% of task-related interactions)
**Figure 7.** Original creative interaction matrix of the organization studied

A Revised Creative Interaction Matrix. After considering our experimental results that suggest the organization has collective power to predict the creative potential of pairs of individuals assigned to design efforts, we revised the original creative interaction matrix to include in each of its cells the average ratings received by the source (of each dyad) on triggering the generation of creative ideas by others. As a result, the cells of the revised creative interaction matrix combine the creative interaction rating given by the recipient and the average rating received by the source from other members of the organization that interacted with him. Note that when a recipient $i$ rates her source $j$ negatively, we mark the dyad $(i,j)$ as a negative creative interaction to enforce the constraint that clusters of creatives include no negative creative interactions. This latter point is consistent with the empirical evidence gathered in our experiment: the average value of creativity assessment during the
design exercise made by individuals who had reported a negative creative interaction prior to the exercise was 4.86, whereas the corresponding value of creativity for individuals who had reported positive creative interactions was 6.01 (a statistically significant difference: \( t = -2.5296, df = 89, p < .001 \)).

In the end, the revised creative interaction matrix \( D_{rev} \) is a function of the original creative interaction matrix \( D \) and the average creative interaction matrix \( D_{avg} \). The cells of \( D_{avg} \) contain the average score received by each actor \( j \) based on his interactions with all other actors to whom he served as a source (except actor \( i \)). (Observe that the cells of the average creativity matrix are determined analogously to how we determined “creative interaction assessed by the class” in our experiment.) Hence,

\[
D_{rev} = f(D, D_{avg}).
\]

The cells of \( D_{rev} \) are determined as follows:

\[
d_{rev,ij} = \begin{cases} 
    d_{avg,ij} & \text{if } d_{ij} = 0, \\
    d_{ij} + d_{avg,ij} & \text{if } d_{ij} \in [4,7], \\
    -1 & \text{if } d_{ij} \in [1,3].
\end{cases}
\] (2)

The cells of \( D_{avg} \) are determined as follows:

\[
d_{avg,ij} = \frac{\sum_{k=1}^{N} a_{kj} (d_{kj}) - d_{ij}}{\sum_{k=1}^{N} a_{kj} - 1},
\] (3)

where \( a_{kj} \) corresponds to cell \( a_{kj} \) of the binary actual communication matrix \( A \).

### 4.3 Step 3: Form Clusters of Creatives

We use the revised creative interaction matrix \( D_{rev} \) as the key input in our clustering analysis. The objective of the clustering analysis is to identify groups of individuals whose task-related interactions (among themselves) have been characterized by the ease of generating creative ideas.

There is an extensive literature on approaches to clustering and graph partitioning. The two main approaches to clustering involve measures that are based either on vertex similarity or cluster “fitness”. Several clustering algorithms are based on similarities between the vertices of a matrix (i.e., the elements that label a matrix such as our creative interaction matrix). These methods are based on the assumption that the greater the vertex similarity, the stronger the need to cluster such vertices together. This type of clustering approach is based on vertex properties that allow a similarity or dissimilarity (also called distance) matrix to be computed (Ben-Arieh and Sreenivasan 1999, Hennig and Hausdorf 2006). The second
approach to clustering, and the one followed in this paper, assesses the overall quality and relevance of a given cluster or of a given global clustering solution based on certain properties of the clusters. Using this approach, clustering algorithms based on graph density measures have been developed to partition an initial graph into subgraphs whose densities are less than or greater than some pre-defined value (Karp 1977, Shi and Malik 2000; Kannan et al. 2004, Kim 2003, Zotteri et al. 2005).

We have formulated the clustering analysis as an optimization problem. The objective is to maximize the sum of positive creative interactions inside clusters. Let $N$ be the total number of actors in the organization and $K$ the number of clusters to be formed. We introduce the affiliation matrix $X$, which is our decision variable, as an $N \times K$ binary matrix whose cells are defined as follows:

$$x_{ik} = \begin{cases} 1 & \text{if actor } i \text{ belongs to cluster } k, \\ 0 & \text{otherwise.} \end{cases}$$

In order to know whether actor $i$ and actor $j$ belong to the same cluster, we multiply $X$ by its transpose $X^T$ to yield $P$, a square matrix of size $N$. Hence,

$$P = XX^T = \{p_{ij}\}, \quad \text{where} \quad p_{ij} = \sum_{q=1}^{K} x_{iq} x_{jq} . \quad (4)$$

Note here that $p_{ij} = 0$ if actors $i$ and $j$ are in different clusters but $p_{ij} \geq 1$ if they belong to at least one common cluster.

Next we define a square matrix $V$ of size $N$ as the entrywise product of $P$ and $D_{rev}$. Thus,

$$V = \{v_{ij}\}, \quad \text{where} \quad v_{ij} = p_{ij} \cdot d_{rev,ij} . \quad (5)$$

Finally, we define the value $z(X)$ of our fitness function (the creativity potential of the clusters of creatives in the organization) as the sum of the values in the cells of $V$. Hence,

$$z(X) = \sum_{i=1}^{N} \sum_{j=1}^{N} v_{ij} = \sum_{i=1}^{N} \sum_{j=1}^{N} p_{ij} d_{rev,ij} = \sum_{q=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{N} x_{iq} x_{jq} d_{rev,ij} . \quad (6)$$

The objective function then becomes $\max_{X \in A} z(X)$, where $A$ is the set of all possible alternatives for the affiliation of actors into clusters.

In addition, the affiliation matrix $X$ is subject to the following five constraints related to our clustering problem.

(C1) *The disjunction of clusters.* An actor may be included in at most one cluster. This means that $P$ must be a binary matrix.
The valid interval for cluster size, \([S_{\text{min}}, S_{\text{max}}]\). We use \(S_k\) to denote the size of cluster \(C_k\). Hence,
\[
S_{\text{min}} \leq S_k \leq S_{\text{max}}.
\]
We view \(S_{\text{min}}\) as having a lower bound of 2 (singletons are not viewed as a “group”). On the \(S_{\text{max}}\) side, the upper bound recognizes that there is a cognitive limit to managing large creative groups. It is also possible to specify the size of one or more clusters by fixing \(S_k\) rather than merely defining its lower and upper limits.

The minimal value of creative interactions within clusters, \(d_{\text{min}}\). In this particular case, we argue that a group designed to be creative should avoid negative creative interactions between its members. This results in \(d_{\text{min}} = 0\). It then follows from constraint (C1) and equation (5) that the exclusion of negative creative interactions from clusters yields
\[
v_{ij} \geq 0 \quad \text{or} \quad V \geq 0.
\]

The number of clusters, \(K\). The decision maker may fix \(K\) in advance, or \(K\) may enter the decision as a variable. When it is not pre-defined, \(K\) may vary in the following interval
\[
\left\lfloor \frac{N}{S_{\text{max}}} \right\rfloor \leq K \leq \left\lfloor \frac{N}{S_{\text{min}}} \right\rfloor \quad \text{where} \quad \lfloor \cdot \rfloor \text{represents the floor function.}
\]

The proposed solution should bring an improvement to the existing organization. The proposed organization should be better than the current one in terms of creativity potential. Thus,
\[
z(\mathbf{X}) > z_{\text{min}},
\]
where \(z_{\text{min}}\) is a function of the value of creative interactions within the current organizational structure. That is: the potential creativity score of the proposed clusters of creatives should be greater than that of the teams currently established within the organizational structures as measured by the creativity score determined via equation (6).

Note that the objective function is quadratic and that our decision variables are integer (since the affiliation matrix is binary). To facilitate the resolution of our quadratic optimization problem, we transform it into a linear optimization problem. The Appendix details how we linearize our objective function and how each of the five constraints is expressed in terms of the transformed formulation. In order to solve our optimization problem, we developed our own subroutines in C-PLEX. Even so, the algorithmic complexity of the problem is high.
(O(2^n – 1)) and problems with more than approximately 22 actors lead to impractical running times. For our application with 58 actors, we therefore fix the number K of clusters and their size (instead of fixing an interval), which dramatically reduces the formulation’s complexity and allows us to find feasible solutions to the problem.

Finally, observe that V is a function of the affiliation of people into clusters; hence, the final affiliation matrix X that maximizes our objective function (subject to preceding five constraints) also defines the clustered creativity matrix C originally discussed in the third step of our structured approach. (In the clustered creativity matrix C, actors who are assigned to the same cluster are sequenced together.) Next we shall use our clustering algorithms to address two types of decisions: (1) finding a team of a given size that maximizes its creativity potential; and (2) reshuffling the entire organization (by changing the membership of the current organizational groups) to maximize its creativity potential.

4.4 Application 1: Forming a Creative Task Force of a Given Size
The first application that illustrates our approach is forming a creative task force of 11 actors. We chose this size because it is the largest group that the current organization is able to handle (the quality assurance group). We aim to find a cluster of actors in the current organization that maximizes the number of positive (past) creative interactions while excluding any negative (past) creative interactions. The solution to this problem is displayed in the matrix of Figure 8(a). The square matrix shown there is labeled with the 11 actors that form a task force of 11 people with the greatest creativity potential in the organization studied. The cells in this matrix show the qualitative scores of creative interaction between these actors as captured in the original creativity matrix (Figure 7). In order to assess qualitatively the goodness of our solution, we compare it with the 11-member group of the current organizational structure (i.e. the quality assurance group) shown in Figure 8(b). The creative task force is potentially more creative than the quality assurance group in the following aspects:

- The creative task force excludes negative creative interactions whereas the quality assurance group has four negative interactions.
- The creativity score of the creative task force is 22% greater than the creativity score of the quality assurance group. The creativity score of a group is calculated based on equation (6). Intuitively, this score measures the creativity potential of a group of
actors based on both the past creative interactions of its members and the creative potential (as assessed by the entire organization) of each of its members.

- The creative task force balances both diversity of background and team familiarity. Unlike the current quality assurance group, which by definition consists of actors who belong to the same group, the creative task force consists of actors who belong to seven distinct groups. However, nearly half (5 of 11) of the members of the creative task force were in the same organizational group in the current organizational structure, which is consistent with previous work suggesting to stir the membership of a team with new members to increase its creative performance (Choi and Thompson 2005, Skilton and Dooley 2010).

4.5 Application 2: Reshuffling the Current Organization

Our second application is to reshuffle the current organizational structure so that the membership of the ten current organizational groups may be reconsidered. In other words, we keep the same number of groups and the same group size, but we allow team members to swap groups in order to maximize the creative potential of the entire organization. This translates into an organizational structure of the same form but with teams consisting of actors that have positive or neutral (but not negative) past creative interactions. Figure 9 displays the clustered creativity matrix that is our solution to this problem.
Figure 9. Final clustered creativity matrix of the organization studied
Now we shift the focus of our analysis to assessing the effort required to transform the current organizational structure in Figure 6 into the alternative organizational structure in Figure 9. *How difficult would it be to reshuffle the current organization?* To address this question, we examine the relationship between the creativity score of the proposed reshuffled organization and the amount of group membership swaps necessary to achieve such a proposed configuration. The rationale behind this comparison rests on the premise that there is an organizational cost associated with changing the current organizational structure. We assume that this organizational cost is proportional to the number of changes in group membership.

To explore the relationship between organizational changes and creativity potential, we augment our clustering algorithm with an additional constraint over a new parameter—*organizational carryover*—that reflects the fraction of dyads that remain in their original organizational group. Organizational carryover varies from 0% (for a fully changed organization) to 100% (for the original organizational configuration). In addition, we compute the improvement in the organization’s creativity potential by determining the improvement in the creativity potential score over the minimum acceptable score for the original organization (which is obtained after reshuffling the original organization to exclude negative interactions from current organizational groups); as before, all creativity scores are calculated based on equation (6). Figure 10 graphs the relationship between organizational carryover and improvement of creativity potential in the organization studied. The plot suggests that there is a trade-off between improving the organization’s creativity potential and retaining its current configuration. First, finding an organizational configuration that excludes negative creative interactions would require (at least) 56% of its members to change groups, which explains why the baseline creativity score starts with a 44% organizational carryover. Then, the figure also shows that improving the creativity potential of the organization by *an additional* 9% requires the formation of new organizational groups whose members would already have interacted, on average, with only 22% of the proposed new group members.
5 Discussion

This paper develops a structured approach to forming creative teams in new product development organizations. Our approach involves three fundamental steps: (1) capturing the organization’s actual formal and informal structure; (2) measuring creative dyadic interactions; and (3) forming clusters of creatives. This paper addresses two fundamental questions related to this approach. First, does implementing this approach lead to better creative performance? And second, how can this approach be implemented in the setting of a real company? With respect to the first question, the working hypothesis that underlies our approach is that positive creative interactions in past task-related activities predict positive creative interactions in future design activities. We exploit the setup of an Executive MBA program to test this hypothesis in a quasi-natural experiment. With respect to the second question, we implement our approach in the new product development department of a company to explore alternative organizational configurations that could improve its creativity potential.

The experimental results provide empirical support for our working hypothesis because we could predict the creativity performance of pairs of individuals working on a team-based creative effort based on their past creative interactions with their colleagues. We find that the best predictor of a creative interaction during the design exercise between actor $i$ (the recipient) and actor $j$ (a team member acting as a source) is not a past positive creative interaction between these two actors as reported by the recipient. Instead, it is the source’s ability to trigger the generation of creative ideas by others (i.e., the average rating of that
capacity by contacts who reported interacting with the source in the past) that best predicts the creativity of an interaction between actors $i$ and $j$ during a product design effort. This experimental result contributes to our understanding of group cognition in engineering design (Cagan 2008): we see that the organization’s collective wisdom is better than its individual members at predicting how pairs of designers will perform when teamed up together in future creative design efforts. This result has crucial implications for the overall approach used to form creative teams: it is not enough to cluster the original creativity interaction matrix whose nonzero cells are the creative interactions reported by the recipient in each dyad. To properly form clusters of creatives, each cell in the (revised) creativity interaction matrix must also include a measure of the source’s perceived ability to trigger creative ideas in others.

We illustrate how our approach may be implemented in a real setting by applying it in the development department of a software development firm. To provide face validity to our approach, we address two types of decisions involving the formation of creative teams: forming a creative task force and reshuffling the existing organizational groups. These decisions are two extremes in the spectrum of decisions associated with forming creative teams while taking into account existing organizational settings. It is instructive that, when evaluating how to improve the current organizational structure of the organization by swapping members across teams, we discover empirical evidence of a trade-off that exists between forming creative teams (a potentially positive change) and reconfiguring the current organizational structure (a potentially costly change).

This paper contributes to the literature on design theory and methodology by integrating streams of research from the domains of creativity and organization design to derive a structured way to form design teams while taking into account the organization’s current structure. From a methodological viewpoint, we combine the use of experimental research and social network analysis to examine whether a single individual or a whole organization predicts well the effectiveness of a colleague with whom one must work closely to generate creative outcomes. From an analytical perspective, we have formulated the challenge of finding clusters of individuals with past positive interactions (while excluding past negative interactions within such clusters) as a linear optimization problem. Future work in this topic will benefit from extending our formulation via alternative constraints—for example, pre-assigning certain members of the team or pre-defining a minimum set of technical expertise that creative teams must have. Our approach will also benefit from additional empirical studies to investigate further the behavioral aspects of implementing a
structured approach that inevitably introduces changes (even if temporarily) in the new product development organization.

Overall, this paper takes a step forward in meeting the challenge of forming teams to maximize creative performance. This challenge is nontrivial and has not been fully addressed in the past—in part because of the conflicting forces driving the creativity phenomenon (Amabile 1996, Sternberg 1999, Linsey et al. 2010, Skilton and Dooley 2010). Creativity in teams is driven to a large extent by diversity and cohesion (Sosa 2010). Our approach avoids forming teams based solely on traditional criteria: the diversity of the potential members’ backgrounds; how well members get along; how long team members have been working together (Choi and Thompson 2005, Skilton and Dooley 2010). Instead, we base our approach on the quality of past creative experiences of individuals in the organization when working together. When looking at the composition of the potentially creative teams, we see that our approach seems to find a balance between diversity and cohesion. In particular, proposed teams are formed by a mix of members that come from different organizational groups (diversity) to join a group of team members who are already familiar with each other because they worked together in the past (cohesion). Forming creative teams is an emerging topic of vital importance for successful new product development. We believe that the approach developed here has important theoretical and practical ramifications, but additional insights remain to be discovered in this nascent area of research.
References


Appendix
We linearize our quadratic optimization problem by defining a three-dimensional matrix $Y$ whose cells uniquely determine whether or not actors $i$ and $j$ belong to cluster $C_k$. The binary variable $y_{ijk}$ is defined as follows:

$$y_{ijk} = \begin{cases} 1 & \text{if actors } i \text{ and } j \text{ belong to cluster } C_k, \\ 0 & \text{otherwise.} \end{cases}$$

The first index corresponds to the affiliation of actor $i$ and the second to that of actor $j$; the third index identifies the cluster $C_k$. The problem becomes linear when we use $y_{ijk}$ (rather than the product of $x_{ik}$ and $x_{jk}$) to determine whether actors $i$ and $j$ belong to cluster $C_k$.

To illustrate the equivalence of using either the $X$ (affiliation) matrix or the $Y$ matrix for our problem, consider the three possible cases concerning the affiliation of actors $i$ and $j$ to cluster $C_k$.

1. **Actors $i$ and $j$ both belong to cluster $C_k$**:
   - $x_{ik} = x_{jk} = 1$ and so $y_{iik} = y_{jjk} = 1$; therefore,
   - considering $x_{ik} \cdot x_{jk} = 1$ is equivalent to considering $y_{ijk} = 1$.

2. **Actor $i$ belongs to cluster $C_k$ but actor $j$ does not**:
   - $x_{ik} = 1$ and $x_{jk} = 0$, so $x_{ik} \cdot x_{jk} = 0$;
   - $y_{ijk} = 1$ and $y_{ijk} = 0$, so $y_{ijk} = \min(y_{iik}, y_{jjk}) = 0$; therefore,
   - considering $x_{ik} \cdot x_{jk} = 0$ is equivalent to considering $y_{ijk} = 0$.

3. **Neither actor $i$ nor actor $j$ belongs to cluster $C_k$**:
   - $x_{ik} = x_{jk} = 0$, so $x_{ik} \cdot x_{jk} = 0$;
   - $y_{iik} = y_{jjk} = y_{ijk} = 0$; therefore,
   - considering $x_{ik} \cdot x_{jk} = 0$ is equivalent to considering $y_{ijk} = 0$.

The two formulations with $X$ and $Y$ are thus equivalent. Just as we obtained the $\{y_{ijk}\}$ variables, we can also derive the $\{x_{ik}\}$ variables by using the relationship $x_{ik} = y_{iik}$.

The objective function of our optimization problem in terms of $\{y_{ijk}\}$ is as follows:

$$\max_{Y \in A} z(Y) = \max_{Y \in A} \left[ \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{N} y_{ijk} \cdot d_{ij} \right];$$

this is a linear problem with a vector $Y$ of $N^2 \times K$ binary variables.

Finally, the constraints of the optimization problem are expressed as follows.

(C1) For each $i \in [1, N]$, we must have $\sum_{k=1}^{K} y_{iik} \leq 1$. 

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(C2) Same as in the original formulation: for each \( k \in [1, K] \), \( S_{\min} \leq S_k \leq S_{\max} \) (or \( S_k \) may be fixed by the decision maker).

(C3) For each \( i, j \in [1, N] \) and \( k \in [1, K] \), we must have \( y_{ijk} \cdot d_{rev,ij} \geq 0 \).

(C4) Same as in the original formulation: the number \( K \) of clusters may be fixed or may vary within \( \left\lfloor \frac{N}{S_{\max}} \right\rfloor \leq K \leq \left\lceil \frac{N}{S_{\min}} \right\rceil \).

(C5) \( \left[ \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{N} y_{ijk} \cdot d_{rev,ij} \right] \geq z_{\min} \), where \( z_{\min} \) is a function of the existing organizational structure.
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