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MANUSCRIPT

Product development team formation: effects of organizational- and product-related factors

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Abstract

Although the performance of new product development (PD) is dependent on the structure and formation of design teams, effective configuration of the PD teams remains largely unexplored. According to social network research, teams are often organized in either closely connected or sparse structure. We conceptualize PD projects as collective problem-solving endeavors and develop a computational model of these projects where a number of designers conduct search over an NK(C) performance landscape. We group the designers in teams with closely connected or sparse structure. We also consider various organizational integration capabilities (i.e., coordinated operations, and common principles) as well as interaction networks among the teams (i.e., acyclical, cyclical, and modular). We use simulation and compare the design performance of teams with different configurations. Our results indicate that the extent by which organizations can effectively integrate design solutions determines the team structure and is likely to result in higher development performance. In addition, the design performance of strategies that employ both closely connected and sparse teams is contrasted with the strategies that use either of these structures. Regardless of the integration capabilities of the PD projects, strategies that simultaneously utilize both closely connected and sparse teams are likely to achieve higher development performance than strategies that only use teams with one particular structure.

Keywords Product development projects · NK(C) landscape · Team structure · Team assembly · Agent-based simulation

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1 Introduction

Teams are essential for problem-solving and the generation of creative ideas in projects (Thompson 2011; Liang et al. 2010). In product development (PD) projects, the use of teams highly depends on product design features. While a small PD team may suffice for developing a simple and bounded product (Fujimoto 1991; Eppinger et al. 1994), complex products—that are becoming rapidly evolving and ubiquitous—tend to use a large number of teams. For instance, over 250 teams were recruited for developing Boeing 777 (Sabbagh 1996).

The structure of teams in a PD project is essential because it significantly influences not only the performance of the teams but also the overall performance of the project (Allen 1977; Guimera et al. 2005). Two common team structures in the literature are closely connected and sparse (Kilduff and Brass 2010). In the closely connected structure (i.e., closure network), a focal actor is surrounded by cohesive social connections, whereas, in a sparse structure (i.e., brokerage), an individual is surrounded by other members belonging to disconnected social groups (Coleman 1990; Burt 1992, 2005). Generally, each of these structures provides distinct performance advantages. Closely connected structures with strong ties are expected to be competent in generating ideas, and sparse networks with bridging ties facilitate the implementation of innovative ideas (Obstfeld 2005; Tiwana 2008). Also, in a closely connected structure, shared third parties (e.g., two engineers having a shared, third connection) create benefits such as induced commitment and trust (Uzzi 1997; Reagans and McEvily 2003), and sparse networks yield information advantage by providing diverse information (Burt 2004).

In the PD context, the formation of teams can be potentially challenging for PD managers due to the complexities of product architectures. First, a PD process includes a multi-level process: the definition and decomposition of product subsystems, then the integration of the developed subsystems (Parraguez et al. 2015). Second, not all subsystems of a product architecture are of equal importance (Ulrich 1995; Baldwin et al. 2014). There are core subsystems of a product that are tightly coupled to other subsystems, whereas peripheral subsystems tend to possess only loose connections to other subsystems (Tushman and Peter 1998). We will discuss these three complexities in the next section.

Because of the challenges discussed above, understanding what team-formation strategy is the most effective is not an easy task for PD managers. Consequently, if they implement an ineffective team-formation strategy, it not only results in a poor design but also wastes potential resources. Therefore, it is essential to understand the impacts of various team configuration strategies. However, despite that, the performance of PD projects is tied with the structure of teams and the complications that the formation of teams poses for PD managers; little research has been conducted on team-formation strategies in PD projects (Sosa and Marle 2013). We aim to fill out this gap by studying performance implications of team assembly strategies. In other words, we investigate the performance effects of adopting two team formations: closely connected teams that we refer to as communicative teams, and sparsely arranged teams that we refer to as diverse

teams. Therefore, we define our first research question as: *Should PD managers build communicative teams or diverse teams?*

In practice, managers of PD projects may consider mixed strategies where both communicative and diverse structures are employed; e.g., communicative teams develop a subset of subsystems, while the rest of the subsystems are developed by diverse teams. While empirical observations show that having both strong ties (that exist in communicative teams) and weak ties (that exist in diverse teams) are essential for creativity and innovation (Capaldo 2007; Tiwana 2008; Zhou et al. 2009; Schultz and Schreyogg 2013), the choice of strategy to achieve maximum performance is unclear. Therefore, our second research question is: *Do PD managers arranging teams with a heterogeneous structure (i.e., both communicative and diverse structures) achieve higher performance than managers arranging teams with a uniform structure (i.e., communicative or diverse structure)?*

In order to address these two questions, we develop an agent-based simulation model based on the well-studied NK landscape model. We focus on the structure of the teams and take into account the integration capability levels of PD projects, as well as the interaction patterns among the teams. We also consider two important features of PD projects: product architecture and complexity level of its design space. Our modeling work helps investigate the macro, firm-level performance consequences of different team assembly strategies in PD projects.

The remainder of this paper proceeds as follows. Section 2 presents a review of the relevant literature. Section 3 describes the mathematical model of designers' collective search effort. The PD performance measures and team-formation strategies details follow these explanations. In Sect. 4, we describe our simulation experiments and report the results. Finally, Sect. 5 presents our conclusions along with the implications and limitations of the study.

2 Literature review

The social and management literatures discuss the benefits for the communicative and diverse structures (Coleman 1990; Obstfeld 2005; Sosa 2011, 2014; Liu and Bin 2017; Xu and Xuan 2010). However, with the complexities of PD projects, the right team-formation strategy remains unclear. Two critical aspects of those projects are organizational integration capability and interaction pattern among subsystems of a product (being developed). The former one is essential as in complex projects, organizational routines are often interrupted over the course of the project, and integration is crucial. The latter one is representative of the complexity of design space.

In this section, we first review the literature on the formation of teams in PD projects. We focus on communicative (dense) and diverse (sparse) structures. We then review PD integration, and work integration mechanisms that are needed to maintain work integrity of the distributed project activities. Finally, we discuss interaction patterns and collective problem-solving perspectives.

2.1 Team-formation in PD projects

The central debate on the structural dimension of social capital revolves around whether more informational and performance benefits are gained from communicative or diverse structures (Kilduff and Brass 2010; Luke and Leonardi 2018; Perry-Smith and Mannucci 2017). The communicative structure provides a supportive environment that is desirable for innovation (Obstfeld 2005). In such structures, common third-parties are frequently present that motivate the designers to engage in design-related interactions, and consequently, they create a collaborative atmosphere needed for creativity (Coleman 1990; Obstfeld 2005). In general, dense structures and third-parties provide trust and information sharing among designers. Hence, teams are expected to have a higher performance. This argument has also been reflected in discussions on R&D teams' arrangements. Specifically, decreasing spatial distance of teams is expected to improve PD performance by improving communication frequency among the teams (Allen 1977; Krishnan and Ulrich 2001; Bardhan et al. 2013). However, high communication may not always improve PD performance. For instance, cyclic interdependencies among designers are common in PD projects (Smith and Eppinger 1997). However, managing those cyclic communicative interactions can be essentially challenging as they can sometime increase design errors (Sosa et al. 2013). Furthermore, with cycles, designers cannot always focus on their own components and may make merely locally optimal decisions.

In a diverse structure, when a focal designer—who has interactions with a large number of designers that tend to be disconnected from one another—is more likely to be creative and innovative. Essentially, this association drives from the fact that a diverse network most probably gives the focal actor access to diverse knowledge, which can be combined into novel outcomes (Burt 2004; Fleming et al. 2007). In addition to the structural features, the knowledge-diversity content of designers' interactions has been considered to improve creativity conditions for design teams (Sosa 2011).

In the PD literature, the communicative and diverse structures are found to be associated with distinct team performance advantages. For instance, in the study of a software development company, Sosa (2011) analyzed engineers' interactions. He found dyadic interactions that channel various knowledge domains are more likely to facilitate the generation of creative ideas. They also observed that when dyadic networks (i.e., common third parties) have cohesion levels below a threshold level, they support the generation of creative ideas. However, a highly cohesive social network of engineers can also negatively affect creativity. By examining other aspects of the same software development data, Sosa (2014) observed positive effects of a social embeddedness of designers' dyadic relationship—combination of tie strength and network cohesion—on the probability that they realize the need for design rework (i.e., corrective or completion actions).

As briefly mentioned in the Introduction Section, the formation of PD teams can be potentially challenging due to the complexities in product architectures. On the one hand, the process of developing a product first includes the definition and decomposition of product subsystems (i.e., conceptual and system level design discussed in Parraguez et al. (2015)), and then the integration of the subsystems.

Each subsystem represents a part of the product architecture and includes a group of components that collectively perform a higher-level function (Gokpinar et al. 2013). For instance, in a vehicle development project, subsystems can be the front suspension, steering wheel, door trim, and front seat, among others. Similarly, in a software development project, subsystems can be groups of source codes (MacCormack et al. 2006). Each of the subsystems in these two examples include a group of components.

On the other hand, according to product architecture concepts, not all subsystems in a product architecture are of equal importance (Ulrich 1995; Baldwin et al. 2014). All complex systems, including PD systems, can be described in terms of their architecture—that is, as a hierarchy of subsystems that in turn have their own subsystems (Simon 1962). Product architecture in particular has been defined as "the scheme by which the function of a product is allocated to its constituent components" (Ulrich 1995). From a product architecture perspective, some subsystems are "core" to system performance, whereas others are only "peripheral" (Tushman and Rosenkopf 1992). Core subsystems have been defined as those that are tightly coupled to other subsystems, whereas peripheral subsystems tend to possess only loose connections to other subsystems (Tushman and Peter 1998). Such core-peripheral oriented structures are common in the development of complex products (MacCormack et al. 2006; Baldwin et al. 2014).

2.2 PD integration

In a complex and distributed environment of projects, organizational routines and norms are often interrupted over the course of the project; therefore, their integration is essentially important. Work integration is defined as mechanisms across the organization and task boundaries to maintain the integrity of the distributed project works from the beginning to the end (Anderson and Parker 2013). Organizations with high integration capabilities can integrate different design solutions proposed by team members and are likely to develop a product using the best design solutions for each subsystem with low costs. Conversely, organizations with low integration capabilities are more likely to converge toward lower quality, more expensive designs. Our differentiation between capable and incapable PD organizations is consistent with the following feature of organizations: workers in teams need to integrate members' knowledge in an ongoing process of mutual adjustment as their work progresses (Kozlowski et al. 1999, Gardner et al. 2012). In other words, knowledge integration makes some teams to be more effective than others by developing dynamic capabilities that enable them to integrate their knowledge in a systematic and reliable way (Gardner et al. 2012).

This view on various level of organizational capability for PD integration can describe the heterogeneity of operational and product performance among PD projects. Usually, operational performance measures the focus on adherence to project schedule and budget, while product performance measures the focus on financial and market performance of an innovative project (Blindenbach-Driessen et al. 2010; Tatikonda and Montoya-Weiss 2001). In addition, operational performance

is generally considered to improve product performance (Tatikonda and Montoya-Weiss 2001). Following this perspective, capable PD organizations can be seen as those that achieve high operational and product performance levels by identifying and integrating best design solutions. However, incapable PD organizations may be conceptualized as the ones with low operational and product performance levels, as they reach only to the average solutions.

Different integration capability levels of PD projects can result from their organizational context and environment. Generally, the organizational context in which teams operate affect their performance by providing them access to technical knowledge and resources to solve their problems (Griffith et al. 2003). In addition, some teams may have access to more resources or face fewer constraints from their organizational context (Young-Hyman 2016). Organizational context should create an environment where the top management translates prioritized strategic themes into actionable goals for middle management. In such environment, the latter coordinate with each other and report upwards on the progress of implementation to enable corrective actions (Ethiraj and Levinthal 2004, Vuori and Huy 2015). Hence, interactions among top and middle management are essential for innovation success. Nevertheless, this can be challenging given that individuals may tend to avoid bringing up issues during their interactions (Vuori and Huy 2015). Such poor mutual understanding between top and middle managers in the innovation process is common (Tripsas and Gavetti 2000; Gilbert 2005)—e.g., see Vuori and Huy (2015) for Nokia's recent innovation challenges.

2.3 Interaction pattern and collective problem-solving perspective

The PD literature shows that a product's architecture—which maps functions of a product to its components (Ulrich 1995)—does not follow a unique structure, and there could be more than one architectures to satisfy the functional requirements of a product (MacCormack et al. 2006). Such architectures probably differ in various performance attributes such as product quality and reliability (Ulrich 1995), partitioning of design tasks and efficiency of development process (Von Hippel 1990). Understanding how such product architectures make performance trade-offs has been a critical topic for scholars (MacCormack et al. 2006). Following this line of research, we examine how different product architectures affect the performance of various team-formation strategies.

In a broader context than PD, empirical work in organizational, social, and technological domains has shown that the interactions among the elements of a system are often patterned, rather than random (see Rivkin and Siggelkow (2007)). Common interaction patterns include small world, hierarchical, and modular (Watts 1999; Rivkin and Siggelkow 2007; Baldwin and Clark 2000). We follow these three patterns for five teams, presented in Fig. 1. Cyclical and acyclical patterns are also known as "core-periphery" and "hierarchical" (MacCormack et al. 2006, 2012; Baldwin et al. 2014). These two patterns capture the extent to which each subsystem depends on itself via other subsystems (Sosa et al. 2013). In acyclical pattern, there is a high degree of cyclicality and one team's design decisions affect its own search

PD subsystem	1	2	3	4	5
1	√	√	√	√	√
2	√	√	√	√	√
3	√	√	√	√	
4	√	√	√	√	
5	√	√			√

(a) Cyclical

PD subsystem	1	2	3	4	5
1	√				
2	√	√			
3	√	√	√		
4	√	√	√	√	
5	√	√	√	√	√

(b) Acyclical

PD subsystem	1	2	3	4	5
1	√	√			
2	√	√			
3			√	√	
4			√	√	
5					√

(c) Modular

Fig. 1 Interaction patterns among five subsystems being developed by five teams

landscape, both directly and via its impact on other teams' search landscape. This structure is absent in an acyclical subsystem interaction pattern. Modular pattern, which is a common feature of product architectures (Ethiraj and Levinthal 2004; Ethiraj et al. 2008), includes modules that are developed independently.

Development of a new product is often conducted in a distributed manner, where teams of designers simultaneously make partially autonomous decisions about product's components that affect the overall product performance (Mihm et al. 2003). This characteristic of PD projects is consistent with the PD conceptualization that decision-makers collectively solve a distributed information-processing problem (Thomke 1997). During the design process, designers engage locally in optimizing features of a component. In addition, due to interactions among the components, designers need to have an ongoing communication process (Mihm et al. 2003; Fisher et al. 2018). Hence, not only a designer's own problem-solving activities, but also the activities of the other peers can affect that designer's activities.

Overall, following the distributed development perspective of the PD projects, we conceptualize these projects as collective problem-solving efforts by some agents (i.e., designers) for a complex problem. Collective problem-solving efforts by interconnected agents have been studied in the literature of complexity and organizational decision-making (Barkoczi et al. 2015). For instance, Lazer and Friedman (2007) used an extended NK landscape model to study how network structure can affect the resulting collective problem-solving attempt. As another example, Fang et al. (2010) contemplated inter-personal network in organizations using a computational model. They illustrated that when subdivided into semi-isolated subgroups, the organization's long-term learning performance is expected to be significantly higher than when the network is not divided into subgroups (or when subgroups have many cross-group links).

3 Model

To understand how team-formation strategies affect PD performance, we build an agent-based simulation model (ABM) of PD based on the well-studied NK landscape (Kauffman 1993). In this section, we set up the mathematical model used to simulate the search process. The constituents of the model are: (1) characterization

of the landscape over which the teams conduct search, (2) organizational arrangement based on which designers interact, and teams' interaction strength measure, (3) the collective search endeavor by designers, (4) the defined performance measures, and finally, and (5) the applied team-formation strategies. We discuss each constituent next.

3.1 The landscape model

We develop our model based on the NK landscape (Kauffman 1993). Consider a product with n_b subsystems. The landscape of subsystem i consists of n_e interacting binary design elements—where 0 and 1 represent different choices for each element. Assuming that all subsystems have the same number of elements (i.e., n_e), the total number of elements for the product is $N = n_b \times n_e$. The state of subsystem i, denoted by a_i is known when the states of its n_e elements are known. Consequently, for each subsystem, there are 2^{n_e} different design configurations. For example, one possible configuration of subsystem i when $n_e = 5$ could be $a_i = (00110)$. Similarly, and from a higher-level perspective, the product state denoted by $A = \left\{ \cup_{i=1}^{i=n_b} a_i | \, i = 1, 2, \ldots, n_b \right\}$ can have 2^N possible design configurations.

For each of 2^N possible design configurations (i.e., design alternatives), there is a defined product performance (e.g., quality). This performance is represented by a fitness value, and defined as the average of contributions of the product subsystems' elements. The contribution of each element x_i of subsystem i is defined such that it depends on: (i) the state of the element x_i itself, (ii) the state of K other randomly-selected elements of subsystem i that interact with element x_i, and (iii) the status of C randomly-selected elements of the other subsystems that interact with that subsystem of element x_i.

In order to generate the landscape, at first, the contributions of the subsystem's elements need to be generated. Let us denote the set of subsystems interacting with subsystem i as DE_i. For instance, if subsystem i interacts with three other subsystems, then the contribution of element x_i depends on $K + 3 \times C$ other elements.[1] These contribution values are drawn from a uniform [0, 1] distribution.[2]

Let $f(x_i|A)$ be the generated contribution of element x_i when the product configuration is A; therefore, the product performance when its configuration is A. This fitness value is represented by a fitness value, $f(A)$ which is the mean of the contributions of all design elements:

$$f(A) = \frac{\sum_{i=1}^{n_b} \sum_{x} f(x_i|A)}{N} \tag{1}$$

[1] The number of required contributions for an element is $2^{K+DE_i \times C}$.

[2] It has been shown that the properties of the fitness landscape are not sensitive to the distribution applied to generate the landscape (Weinberger 1991).

3.2 Organizational structure and teams interaction strength

We generate an organizational network or team arrangement using the "connected caveman" structure. This was developed by Watts (1999), and recently used by Fang et al. (2010) to create interpersonal organizational structures. In a network representation of a PD project, nodes (i.e., designers) correspond to the designers in teams. In addition, an edge indicates organizational relationship between two designers. In the caveman structure, the designers of each PD team are clustered and minimally connected to the other PD teams.

Assume there are n_b teams and each team j is developing subsystem $i(i = j)$. Moreover, each team j is comprised of n_q number of designers shown by $D_j = \left\{ d_q^j | \, q = 1, 2, .., n_q \right\}$. Each designer is an agent in our model. We assume that there is a fixed number of teams for development of each subsystem. Let us define the subset of designers D_q^j to be designers $d_{q'}^{j'}$, who have organizational interactions with designer d_q^j. This set for each designer is determined according to the organizational network structure.

As discussed earlier, each team is developing a particular subsystem with varying interaction and criticality level. To model this, the subsystem' interaction intensity with all other subsystems is considered. Toward that end, we define a "subsystem interaction strength" measure that is based on two measures: (a) how many subsystems affect the fitness value of subsystem j (subsystem $i = j$) that is being developed by team j (i.e., $|DE_j|$), and also, (ii) how many subsystems' fitness values are affected by subsystem j that is being developed by team j (i.e., $|SI_j|$). Specifically, we define interaction strength measure, as follows, that captures the overall influence of team j in the space of a complex PD project. In Eq. 2, we define a weight parameter $W > 1$. This parameter is a fixed integer, which we set experimentally to enable us to differentiate between two types of interactions. In one type of interaction, a focal team influences other teams, whereas, in other types, a focal team is impacted by other teams. Interaction strength measure m_j is similar to the other defined constructs in the literature [i.e., Fan-out and Fan-In measures in (Baldwin et al. 2014)] for the visibility matrix which calculates the extent of redesign iterations/efforts for the changes in a particular element of a system (Sharman and Yassine 2004; MacCormack et al. 2006; Baldwin et al. 2014).

$$m_j = \frac{|DE_j| + W \times |SI_j|}{(1 + W) \times n_b} \tag{2}$$

The defined measure enables us to define scenarios in which the teams tend to have particular structure and behaviors. That is, teams are established to have particular features with a probability that is a function of the interaction strength measure m_j (e.g., increasing or decreasing in m_j).

3.3 Design process as collective search

To materialize various social structures in this model, designers' absorptive capacity (Cohen and Levinthal 1990) as well as the designers' expertise are varied

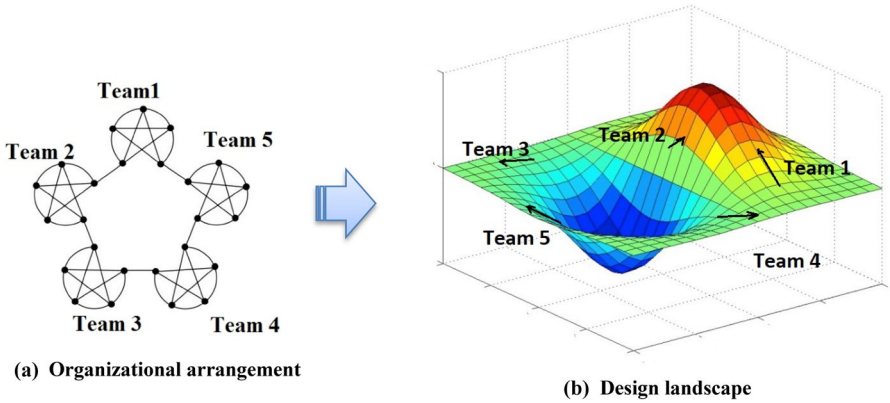


Fig. 2 Caveman network (Watts 1999; Fang et al. 2010) for PD teams' organizational arrangement (left) that affects a collective search effort over the design landscape (right). The paths shown on the right panel are just illustrative of search trajectories of teams over time

across teams (more details are provided in Sect. 3.4). Absorptive capacity is the capability to understand shared design solutions by the other designers. Cohen and Levinthal (1990) defined absorptive capacity as "… prior related knowledge confers an ability to recognize the value of new information, assimilate it, and apply it to commercial ends". Therefore, different team-formation strategies are considered to affect designers' absorptive capacity and their expertise distribution, who are collectively conducting a search over a performance landscape (see Fig. 2).

We conceptualize a PD project as a parallel collective search process conducted by the designers of PD teams. That is, the design solution of each designer, at any time t, is regarded as a position over the product landscape with N decisions (i.e., a design alternative among 2^N alternatives), and each focal designer conducts his own search while communicating with other designers at some occasions.

In our model, initially and at time $t = 0$, each designer d_q^j is assigned a randomly selected design solution or state $s_{q,j}^0$ and his fitness value is calculated. Moreover, at each subsequent time t, each designer d_q^j engages in either design improvement through a local search or communicating design solutions as follows (Lazer and Friedman 2007; Lin 2014). At first, at each simulation time, designers engage in conducting a local search. If the local search endeavor was successful, and a focal designer finds a superior solution, then he will not perform any other task at time t. However, with unsuccessful local searches the set of designers whose local search processes do not result in finding superior solutions get involved in communicating with the other similar designers (i.e., whose local searches were unsuccessful at each time t).

According to the local search process, a focal designer changes one of the states of the design elements in his expertise domain, i.e., $x_i \in EX_q^j$, from 0 to 1 or vice versa. That generates a new alternative $\tilde{s}_{q,j}^{t+1} \in S$ which the designer accepts if the resulting alternative has a higher fitness value; thus:

$$s_{q,j}^{t+1} = \tilde{s}_{q,j}^{t+1} \text{ if } f(\tilde{s}_{q,j}^{t+1}) > f(s_{q,j}^{t}) \tag{3}$$

Otherwise, designer d_q^j retains the previous alternative and $s_{q,j}^{t+1} = s_{q,j}^{t}$.

Once all the communicating designers at time t are recognized, we create pairs of communicating designers who have organizational interactions (based on the structure discussed in Sect. 3.2). In doing so, there could be few designers for whom communicating partners cannot be found. Those unpaired designers, then, retain their design solution (i.e., position over performance landscape) for the next time period. Assume designers $d_{q'}^{j'}$ and $d_{q''}^{j''}$ are selected for communication at time t, and $d_{q''}^{j''} \in D_{q'}^{j'}$, and also assume the latter has a higher fitness than the former, i.e., $f(s_{q'',j''}^{t}) > f(s_{q',j'}^{t})$. Then, the state of each element of the design solution of designer $d_{q''}^{j''}$ is imitated with probability $AC_{q'',q'} \in [0,1]$, and, is used by designer $d_{q'}^{j'}$, at the next time period. In addition, designer $d_{q''}^{j''}$ retains the current design alternative for the next period, $s_{q'',j''}^{t+1} = s_{q'',j''}^{t}$. This process is repeated for all designers who are communicating with each other at time t.

The defined parameter $AC_{q'',q'}$ represents designers' absorptive capacity, and shows the percentage of the design solutions (e.g., decision string [0,1,0,1]) of designer $d_{q''}^{j''}$ that are imitated by designer $d_{q'}^{j'}$ and is inversely associated with the knowledge and background diversity level in teams (i.e., the highly diverse team has low absorptive capacity where a low percentage of design solutions are communicated among designers). Since absorptive capacity can be defined at different levels, e.g., individual, team, our defined parameter and modeling assumption appear to be plausible.

When a designer attends to his own design and conducts a local search, his expertise domain can significantly affect the search process effectiveness. Following the former modeling assumptions (Kavadias and Sommer 2009), we assume a focal designer d_q^j is knowledgeable about a subset of n_e design elements of subsystem i, that is denoted by $EX_q^j \in n_e$ elements of subsystem i. Additionally, the expertise domain of each designer is defined to cover only one design element, $\left|EX_q^j\right| = 1 \, \forall d_q^j$.

3.4 Teams with different structures

When PD teams have a closely connected and cohesive structure, designers are more likely to have higher absorptive capacity, and, also possess similar knowledge domains. However, in teams with sparse structure, designers have diverse expertise, and their communication is less likely to be effective.

At first, we consider PD projects where managers apply similar (homogeneous social structure) structures for all PD teams. To this end, teams with two different structures are elaborated. In these projects, the team features like designers' communication effectiveness and expertise distribution are unrelated to the teams' subsystems features like its interaction strength measure (i.e., m_j that was defined in Sect. 3.2). Let $p_{dd}^{y} \in [0,1]$ denote the diversity level that policy y applies for team formation. Then, we assume that the team diversity level is: (i) adversely related to the probability that the designers in teams have similar expertise domain, or

mathematically, $P(EX_q^j = EX^j) = 1 - p_{dd}^y \quad \forall d_q^j$ and $\left|EX_q^j\right| = 1$; and, (ii) adversely associated with the designers' absorptive capacity level, or mathematically, $AC_{q'',q'} = 1 - p_{dd}^y \quad \forall d_{q'}^{j'}, d_{q''}^{j''}$.

We define *"communicative teams"* to be assembled by considering a low diversity level, $p_{dd}^1 \approx 0$. As a result, the designers' absorptive capacity is high and, also designers have similar expertise with a high probability. On the other hand, *"diverse teams"* are assembled with a sparse structure. Hence, a high diversity level, $p_{dd}^2 \approx 1$ is enforced. Consequently, designers' absorptive capacity is low and, also with a low probability, designers have similar expertise domains.

We investigate the performance of PD projects that simultaneously utilize both "communicative and diverse teams". In this regards, we elaborate two PD systems that use both communicative and diverse teams. In these PD systems with "heterogeneous team structures", designers' absorptive capacity and their likelihood to have similar expertise are associated with the teams' interaction strength measure (m_j that was defined in Sect. 3.2). To that end, we also use core and peripheral concepts that have been defined in the literature (Tushman and Rosenkopf 1992; Tushman and Peter 1998). This enables us to investigate whether performance of PD systems with heterogeneous teams are affected by the team structure of those who are developing subsystems with higher/low interactions strength.

We define one PD system with heterogeneous teams where teams with higher interaction strength (who develop central subsystems) are formed with a more closely connected structure. That is, a set of designers who have shared third-parties or simply they cohesive structure—are allocated to more central subsystems. Stating it differently, the more teams have sparse and disconnected structure, the less central/core subsystems they design. Hence, we refer to these teams as "diverse teams developing peripheral". The following assumptions are considered to form diverse teams developing peripheral: (i) probability that designers in team j have similar expertise domain is increasing in their interaction strength, or mathematically, $P(EX_q^j = EX^j) = m_j \quad \forall d_q^j$, and $\left|EX^j\right| = 1$, and, (ii) the designers' absorptive capacity is increasing in their interaction strength: $AC_{q'',q'} = m_j \quad \forall d_{q'}^{j'}, d_{q''}^{j''}$.

The other PD system with heterogeneous teams is formed with teams that are closely connected and subsystems that have lower interaction strength. In other words, following this strategy, diverse teams develop a core subsystem with higher number of interactions. We refer to those teams as "diverse teams developing core". More precisely, diverse teams developing core are characterized as: (i) probability that designers in team j have similar expertise domain is decreasing in their interaction strength, or mathematically, $P(EX_q^j = EX^j) = 1 - m_j \quad \forall d_q^j$ and $\left|EX^j\right| = 1$, and, (ii) the designers' absorptive capacity is decreasing in their interaction strength: $AC_{q'',q'} = 1 - m_j \quad \forall d_{q'}^{j'}, d_{q''}^{j''}$. The team formation scenarios are listed in Table 1.

3.5 PD performance

As a collective endeavor, design solutions should be acknowledged and accepted by all members of a team, and they need managerial approval. Thus, not only

Table 1 Different team formation scenarios

Team formation	Parameters setup	Social structure	Scenario
Communicative teams	$P(EX_q^j = EX^j) = 1 - p_{dd}^y \quad \forall d_q^j$ and $\left\lvert EX_q^j \right\rvert = 1$; $p_{dd}^1 \approx 0$	Homogeneous	Designers' absorptive capacity is high and, also designers have similar expertise with a high probability
Diverse teams	$P(EX_q^j = EX^j) = 1 - p_{dd}^y \quad \forall d_q^j$ and $\left\lvert EX_q^j \right\rvert = 1$; $p_{dd}^2 \approx 1$	Homogeneous	Designers' absorptive capacity is low and, also designers have similar expertise with a low probability
Diverse teams developing peripheral	$P(EX_q^j = EX^j) = m_{j_{\prime\prime}} \quad \forall d_{\prime\prime}^j$, and $\left\lvert EX^j \right\rvert = 1$; $AC_{q'',q'} = m_j \quad \forall d_{q'}^{j'}, d_{q''}^{j''}$	Heterogeneous	Designers who have cohesive structure are allocated to more central subsystems
Diverse teams developing core	$P(EX_q^j = EX^j) = 1 - m_{j_{\prime\prime}} \quad \forall d_{\prime\prime}^j$, and $\left\lvert EX^j \right\rvert = 1$; $AC_{q'',q'} = 1 - m_j \quad \forall d_{q'}^{j'}, d_{q''}^{j''}$	Heterogeneous	Designers who have cohesive structure are allocated to more central subsystems

discovery of a design solution, but also, its acceptance in the organization needs to be considered. Specifically, the latter process requires managerial and organizational resources. This can be discussed from the integration perspectives (Anderson and Parker 2013; Mishra and Sinha 2016). This aspect emphasizes the fact that knowledge in projects are complex. Consequently, in a distributed environment like projects, organizational routines and norms are often interrupted over the course of project. Hence, some mechanisms across organization and task boundaries are necessary to integrate the distributed project work (Anderson and Parker 2013).

To materialize the effectiveness of firms in acceptance and integration of a superior solution among a team's designers, we define two quality measures. One measure of product quality uses the best design solution discovered by designers of each team for its subsystem. The second quality measure is the average fitness of all design solutions found by all designers. An organization with a high capability of integrating different design solutions—proposed by team members—is likely to develop a product using the best design solutions for each subsystem with low costs. In other words, firms with a high integration capability presumably can apply the former quality scale. However, when PD systems are less capable (e.g., unable to cope with high integration costs), they are more likely to converge toward lower quality designs. In our paper, that lower product design is represented by the second quality scale or the average of design solutions of all.[3]

In this paper, the first quality scale that uses the best design solutions for each subsystem is called the best quality measure. Let fitness value Q_{ij}^t indicate the quality of subsystem i at time t that is being developed by team j (with $i = j$). Then, the overall best product quality at time t is the average of subsystem's quality:

$$PQ^t = \frac{\sum_{j=1}^{j=n_b} Q_{ij}^t}{n_b} \text{such that } Q_{ij}^t = \underset{q}{Max}\,[f(s_{q,j}^t)] \text{ for } \forall d_q^j \in D_j \tag{4}$$

The second quality scale, or average quality, calculates the average fitness of all the design solutions found by the designers. Thus, the overall product quality can be represented as:

$$V^t = \sum_{j=1}^{n_b} \sum_q f(s_{q,j}^t) \text{ for } \forall d_q^j \in D_j \tag{5}$$

[3] In a very abstract view, the first quality measure represents the capability of a PD system to analyze all design solutions, and select the best ones found for each subsystem. Whereas, the second quality scale indicates less capable systems that use lower amount of resources, and converge toward the average fitness of all the designers' solutions.

Table 2 Different Landscape Scenarios

K	C	Scenario
$n_e - 1$	$n_e - 1$	Elements of both a subsystem and different subsystems are intensely interdependent
1	1	Elements of both a subsystem and different subsystems are mildly interdependent[a]
$n_e - 1$	1	Elements of each subsystem are intensely interactive, whereas, elements of different subsystems have a low number of interactions
1	$n_e - 1$	Elements of a subsystem are intensely interactive, whereas, elements of different subsystems have a low number of interactions

[a]This has smallest number of interactions among elements, hence, its landscape is smooth. The other three configurations have more rugged landscapes, as there are a higher number of interactions among elements

4 Experiments and results

In this section, we describe the experimental setup (written using Python programming language) and report the results. One set of parameters in our model is related to the general setting of PD projects. The parameter N in the NK simulation model is the total number of elements in the landscape: $N = n_b \times n_e$. In our experiments, we assume that the product consists of $n_b = 5$ subsystems and that each subsystem's landscape consists of $n_e = 4$ interacting elements, respectively; hence, $N = n_b \times n_e = 4 \times 5 = 20$. Furthermore, we assume there are $n_q = 5, 7$ number of designers in each of the teams. Hence, a PD project with five subsystems, includes $5 \times 5 = 25$ ($5 \times 7 = 35$) designers (i.e., agents) in total.

The second type of parameters define the PD landscape features. The ruggedness of the search landscape depends on both parameters K and C—in other words, on how interdependent the elements of the subsystems are (Levinthal 1997). Low values of K and C imply that the contribution of one element is rather limited and independent of the other elements; hence the landscape is relatively smooth and a change in the state of one element does not significantly affect the fitness of others. However, if the values of K and C are high, then the fitness landscape becomes more rugged; here a change in the state of one element may have a significant effect on the fitness values of other elements. In such landscapes, an incremental search process may stop at a local optimum.

To cover both smooth and rugged landscapes, we assume parameters K and C to be either 1 or $n_e - 1$ (i.e. the number of elements of a subsystem minus one). Possible configurations based on these two inputs are presented in Table 2.

It is worth noting that the four defined PD project settings, shown in Table 1, represent the architectural knowledge of a firm. In other words, the interaction intensity within and between subsystems, or K and C respectively, represent the organization effectiveness in managing interactions. When, within and between subsystem interactions are light and intense ($K = 1$, $C = n_e - 1$), the element interactions have not been managed properly—as each team is developing a subsystem that its elements, in a large extent, are independent. In the other project configurations, within subsystem interactions are more intense than, or at least similar to, that of between

subsystem interactions. Hence, these interactions among the elements of these products are managed more properly.

Subsystems in a PD project may relate to each other in different architectures (patterns). Figure 1 in Sect. 3.2 shows the three patterns, cyclical, acyclical and modular pattern, that we use in our experiments for $n_b = 5$ teams.[4]

4.1 Experiment 1: uniformly assembled teams

Managers may use the same policy to form teams for all subsystems. In our first set of experiments, we investigate whether closely connected and less diverse teams result in higher PD performance than that of sparse and diverse teams. Will PD projects have superior performance if they use one of these team-formation strategies? In addition, does the answer to this question depend on either the interaction pattern among product subsystems or the level of interactions intensity? How about the integration capability of firms?

We compare the performance of a PD project with two team structures: (i) communicative teams who have high absorptive capacity and similar expertise, (ii) diverse teams whose communication is less effective and have diverse expertise. To that end, we assume the former and latter assign low $p^1_{dd} = 0.1$ and high $p^2_{dd} = 0.9$ diversity levels, respectively. We compare these strategies based on both the best and average quality measures that are defined in Eqs. 4 and 5. We simulate each scenario for a fixed number of time periods and record the performance measures of all the teams.

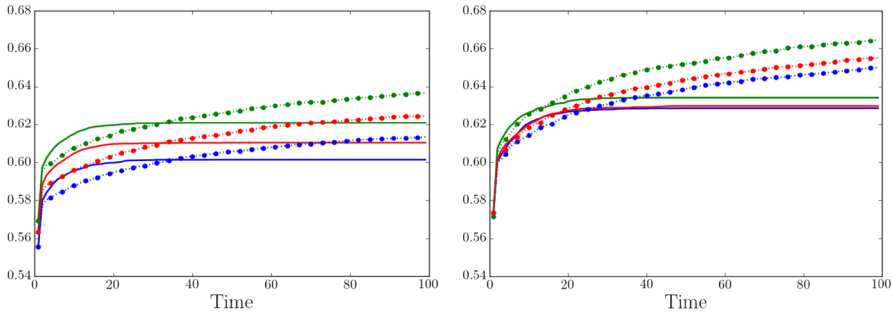
For each combination (PD setting and subsystems' interaction pattern), we generate 100 landscapes. For each landscape, we create the corresponding PD project scenario (e.g., with communicative teams) and let teams conduct the search process for 100-time periods. This process is repeated for each of the 100 landscapes. Then, the performance at each simulation time is defined as the average performance at that time period across all landscapes.

Graphs[5] in Fig. 3 depict the best quality performance (PQ^t in Eq. 4) of PD projects with the $K = C$ setting.[6] According to panels (a)-(d), deploying diverse teams results in higher long- term performance than using communicative teams. This holds for all PD settings with various subsystems interaction patterns and different interaction intensity levels (i.e., within-team, K, and between-team C interaction levels). However, across all panels, in the short-run, PD systems with communicative teams outperform those with diverse teams. As discussed earlier, PD systems need to have a high integration capability (i.e., can manage integration costs) to attain

[4] The patterns for $n_b = 7$ teams are exactly the same pattern as those shown in Fig. 1. Note that modular pattern is perfectly modular with every two teams having interactions only with themselves, and do not interact with any other team.

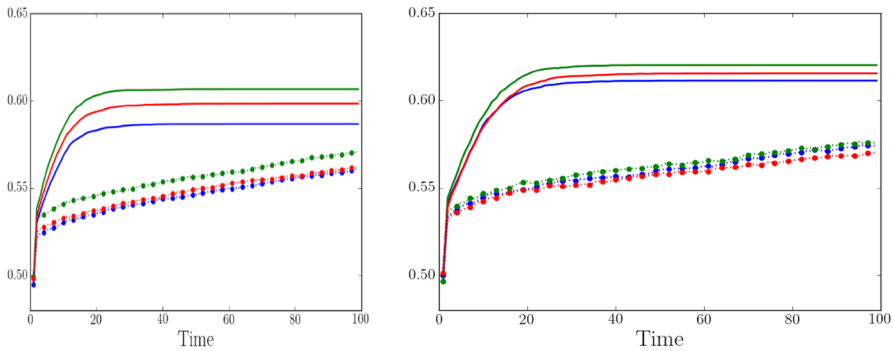
[5] In all Figs. 3, 4, and 5, the following features are common: (1) each point is the average performance of 100 simulation runs, and (2), subsystems interacting in modular (blue), cyclical (green), and acyclical (red); and also $n_b = n_q = 5; n_e = 4$.

[6] The complete set of results are reported in the Online Appendix.



(a) ($K = 1$ and $C = 1$) **(b)** ($K = 3$ and $C = 3$)

Fig. 3 The best quality performance of PD projects. *Note* Communicative teams represented by solid and continuous line; diverse teams represented by dotted lines



(a) ($K = 1$ and $C = 1$) **(b)** ($K = 3$ and $C = 3$)

Fig. 4 The average quality performance of PD projects. *Note* Communicative teams represented by solid and continuous line; diverse teams represented by dotted lines

the best quality performance levels. Thus, for such projects, diverse teams tend to achieve superior best quality solutions than those of communicative teams.

Graphs in Fig. 4 depict the average quality performance (V^t in Eq. 5) of PD projects with the $K = C$ setting and the complete set of results are reported in the Online Appendix. Plots indicate that when firms can attain average quality performance, two team-formation strategies result in different design performances. For all PD settings (e.g., interaction pattern, K, C), communicative teams tend to have higher average quality solutions than those of diverse teams. Interestingly, when PD systems are incapable, and consequently, can only attain average quality design solutions, communicative teams perform better than diverse teams. These results are different from those for projects capable of converging toward best quality designs. Hence, our result indicates that superior team-formation strategy changes with the PD system's capability level.

To investigate the patterns observed in the graphs, paired t-tests are conducted to statistically compare performances across projects. Because each project type

Table 3 Paired *t* tests comparing the best quality performance of PD systems with communicative teams and those with diverse teams

Inputs			Pattern	t value	Pattern	t value	Pattern	t value
n_q	K	C						
5	1	1	Modular	– 7.892*	Cyclical	– 9.125*	Acyclical	– 7.292*
	1	3		– 11.698*		– 11.47*		– 8.157*
	3	1		– 8.249*		– 12.305*		– 8.628*
	3	3		– 10.094*		– 15.343*		– 11.565*
7	1	1		– 5.118*		– 8.104*		– 6.555*
	1	3		– 5.888*		– 10.517*		– 10.636*
	3	1		– 7.564*		– 8.34*		– 8.939*
	3	3		– 7.603*		– 10.246*		– 8.481*

Asterisk indicates a 1% significance level

(e.g., diverse team strategy and $K = C = 1$) is simulated on the same landscape as other type (e.g., communicative team strategy and $K = C = 1$), the observations in one sample (e.g., performance of a project with diverse teams) can be paired with observations in another sample (e.g., performance of a project with communicative teams). As the project's performance constantly changes over time, we used the average PD performance in the last 10-time periods as performance measure in our statistical tests. We have conducted two paired t-tests. The null hypothesis for the first set of paired t-tests expects the mean of best quality of a system with diverse teams to be equal to that of a system with communicative teams.[7]

The results of the first set of paired t-tests are provided in Table 3. The results on p-values of all shown t-tests are provided in Online Appendix (Tables 10–14). Clearly, the observed patterns in Fig. 3 are reflected in the results. Specifically, when comparing the bests design solutions found by communicative and diverse teams, those of the former teams tend to have lower fitness values than those of the latter teams. Across all PD settings (e.g., subsystems pattern, K), this result is robust and holds true.

The null hypothesis of the second set of paired t-tests expects that there is no difference between the mean of average quality of a PD project with diverse teams and that of a project with communicative teams. These tests' results are shown in Table 4. Consistent with the graphs in Fig. 4, regarding the average design solutions found by communicative and diverse teams, those of the former have higher fitness values than those of the latter. This holds for all PD settings, e.g., subsystems patterns,K, C.

Our experimental results imply that depending on the integration capability and costs, PD managers should use either of the diverse and communicative teams. If

[7] In other words, the first set of paired t tests, compare PQ^t in Eq. 4 of diverse teams with that of communicative teams. Therefore, positive and negative t values indicate communicative teams are doing, respectively, better and worse than diverse teams.

Table 4 Paired t tests comparing the average quality performance of PD systems with communicative teams and those with diverse teams

Inputs			Pattern	t value	Pattern	t value	Pattern	t value
n_q	K	C						
5	1	1	Modular	14.724*	Cyclical	18.423*	Acyclical	16.213*
	1	3		14.044*		19.551*		18.781*
	3	1		16.11*		20.671*		14.725*
	3	3		16.027*		20.882*		23.895*
7	1	1		21.176*		28.842*		29.685*
	1	3		27.541*		34.242*		33.736*
	3	1		31.487*		32.575*		33.237*
	3	3		31.508*		38.892*		33.651*

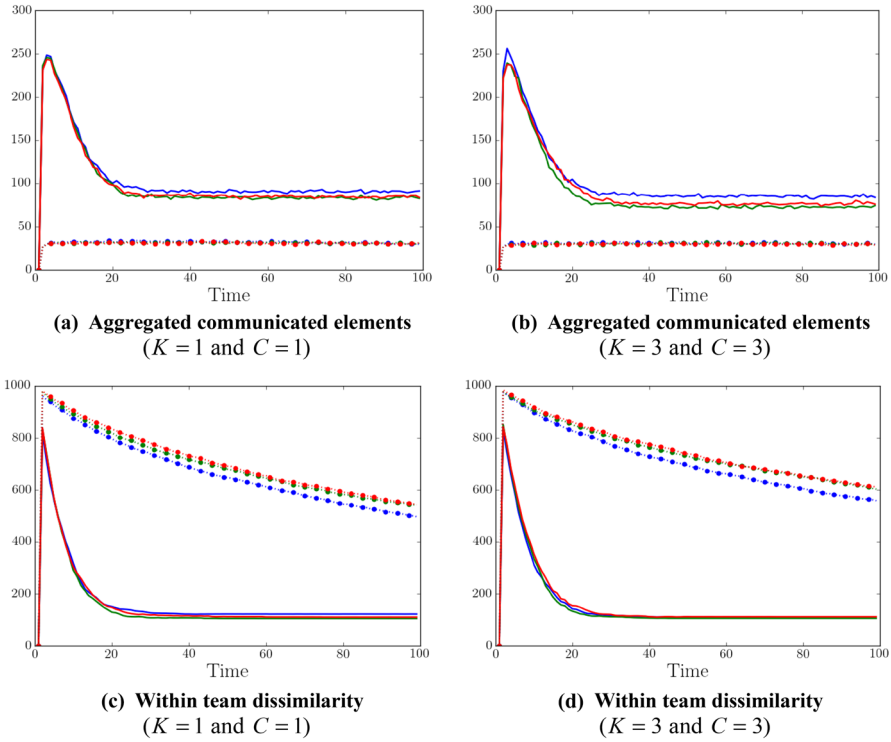
Asterisk indicates a 1% significance level

the PD systems can efficiently integrate different design solutions (e.g., low integration cost), diverse teams with a high absorptive capacity should be assembled. However, for organizations that have inefficient integration processes, this team-formation strategy may not be superior. In the cases that, large amount of resources (e.g., costs) are necessary to integrate different design solutions, managers should build communicative teams. The rational for this strategy is that, according to the average quality measure, communicative teams tend to find design solutions with higher fitness values than those of the communicative teams.

It is worth noting why the two team-formation strategies make different performance trajectories/patterns. With deploying communicative teams, as designers are very likely to have similar expertise, the PD project confines its collective search effort to only parts of the whole landscape. As an example, consider an extreme case, when all designers in each team have the same expertise, or mathematically, $EX_q^j = EX^j \quad \forall d_q^i \in D_j$, and, there are five designers ($n_q = 5$) in each of the five ($n_b = 5$) teams, developing subsystems with $n_e = 4$ elements. Then, such a collective search effort, and in its full reach, eventually, can examine only $25 \times 2^5 = 800$ design solutions, which is $\frac{800}{2^{20}} = 0.076\%$ of the whole landscape.

Despite its confined search, using communicative teams has its own advantages. This strategy forms teams with high absorptive capacity, and their communications are highly effective. Thus, when a designer finds a superior design solution, that solution, quickly, and to a high extent, is communicated to the other designers.

With an imperfect imitation of design solutions, a number of designers converge and get close to the set of designers with superior designs (e.g., local optima). That number of designers that converge toward superior solutions (i.e., with high fitness values), by partially imitating their design solutions, is likely to be high at the initial stages of the PD process since the designers' solutions are more likely to be inferior (i.e., the solutions are randomly selected). However, at the later steps of the PD process, since designers' solutions have improved through either local search or communication, they move back and forth between solutions near superior ones. That



(a) Aggregated communicated elements ($K = 1$ and $C = 1$)

(b) Aggregated communicated elements ($K = 3$ and $C = 3$)

(c) Within team dissimilarity ($K = 1$ and $C = 1$)

(d) Within team dissimilarity ($K = 3$ and $C = 3$)

Fig. 5 The aggregated communicated elements and within-team dissimilarity of PD projects. *Note* Communicative teams represented by solid and continuous line; diverse teams represented by dotted lines

phenomenon happens as designers partially imitate solutions of a superior designer at one time, and then, later at another time, they partially imitate design solutions of another superior designer. Those latter set of design solutions near a local peak is known as basin of attractions (Kauffman 1993; Levinthal 1997).

By building diverse teams, as designers are very likely to have different levels of expertise, the PD project benefits from a broad collective search effort that covers most of the whole landscape. Consider an extreme case, when all designers in each team have completely diverse expertise, or mathematically, $EX_q^j \cap EX_{q'}^j = \varphi \quad \forall d_q^j, d_{q'}^j \in D_j$. Then, such a collective search effort can literally examine the whole landscape. Nevertheless, such a search effort is limited by factors such as available resources (e.g., simulation time).

Despite its wide collective search, usage of diverse teams has its own drawbacks. This strategy forms teams with low absorptive capacity, and their communications are highly ineffective. Thus, although a designer may find a superior design solution, that design, is communicated slowly and ineffectively to the other designers. Hence, designers are less likely to benefit from the other designers' search effort.

The above arguments are confirmed by the following graphs in Fig. 5 (these graphs illustrate results for PD projects with and, and graphs for all PD settings are

provided in the Online Appendix). We observe similar patterns for all PD settings. Panels (a-left) and (b-right) show the number of design elements communicated between designers at each time. Interestingly, the number of design elements communicated between designers in communicative teams increases at first and then decreases sharply. Conversely, the number of communicated design elements for diverse teams show stable patterns, indicating that designers' tendency to communicate does not change throughout the PD process.

Additionally, we have calculated "within-team dissimilarity" of designers' solutions (see Fig. 5). Similar measures have been used in the literature (Fang et al. 2010, Schilling and Fang 2014), and we make pairwise comparisons of all n_q designers in each team. Specifically, each of N design elements of those designers are compared using the following formula. In this equation, $\omega^j_{q1,q2,e}$ takes the value 1, if element e of solutions of designers d^j_{q1} and d^j_{q2} are different, and the value 0, otherwise:

$$Dis = \sum_{j=1}^{n_b} \sum_{q1=1}^{n_q} \sum_{q2=1}^{n_q} \sum_{e=1}^{n_e} \omega^j_{q1,q2,e} \quad \forall d^j_{q1}, d^j_{q2} \in D_j \tag{6}$$

Panels (c) and (d) show within-team dissimilarity in Eq. 6 over time. According to these graphs, as designers find local optimum or superior solutions on the landscape, their solutions are imitated by the other designers. Consequently, within-team dissimilarity is decreasing for both communicative and diverse teams. By building communicative teams, within-team dissimilarity decreases quickly and, stabilizes at a very low level. On the other hand, within-team dissimilarity decreases at a lower rate when diverse teams are deployed.

Overall, the aggregated communicated elements and dissimilarity graphs in Fig. 4, are consistent with our conjectures on the performance effects of using communicative and diverse teams. While communicative teams benefit from search effort of the other designers who have found superior solutions, diverse teams are more likely to find more superior solutions by having a broad and powerful collective search effort.

To identify micro-mechanisms that drive our results, we have conducted some other experiments. Recall that team-formation strategies are characterized by considering two aspects of the designers' search process: the absorptive capacity level ($AC_{q'',q'}$) and the probability of designers having similar expertise domains $P(EX^i_q = EX^j)$. To that end, the corresponding values of these two features are fixed at a high value close to 1, or, alternatively, a low value near 0. Hence, these two features can be the main drivers of the previously seen performance behaviors. To clarify this argument, we have conducted two set of experiments, and their results are provided in the Online Appendix.

In one set of experiments, we keep the absorptive capacity level fixed $AC_{q'',q'} = AC \in [0, 1]$, and then, redefine the two team-formation strategies: (i) communicative teams, or closely connected teams are deployed only by assuming a high probability for having similar expertise domains for all designers, and, (ii) diverse teams or sparsely structured teams are assembled only by considering a low

probability for designers having similar expertise domains. Next, we simulate PD systems with these two strategies for team assembly. The results are provided in the Online Appendix section.

In a similar experiment with different setups, we keep the probability by which designers have similar expertise domains fixed $P(EX_q^j = EX^j) = P(EX_{q'}^j = EX^j) \in [0, 1]$, and then, redefine the two team-formation strategies: (i) communicative teams or closely connected teams are deployed only by assuming a high absorptive capacity level for designers, and, (ii) diverse teams or sparsely structured teams are assembled only with consideration of a low absorptive capacity level for designers. Next, we simulate PD systems with these two strategies for team assembly. The results are provided in the Online Appendix.

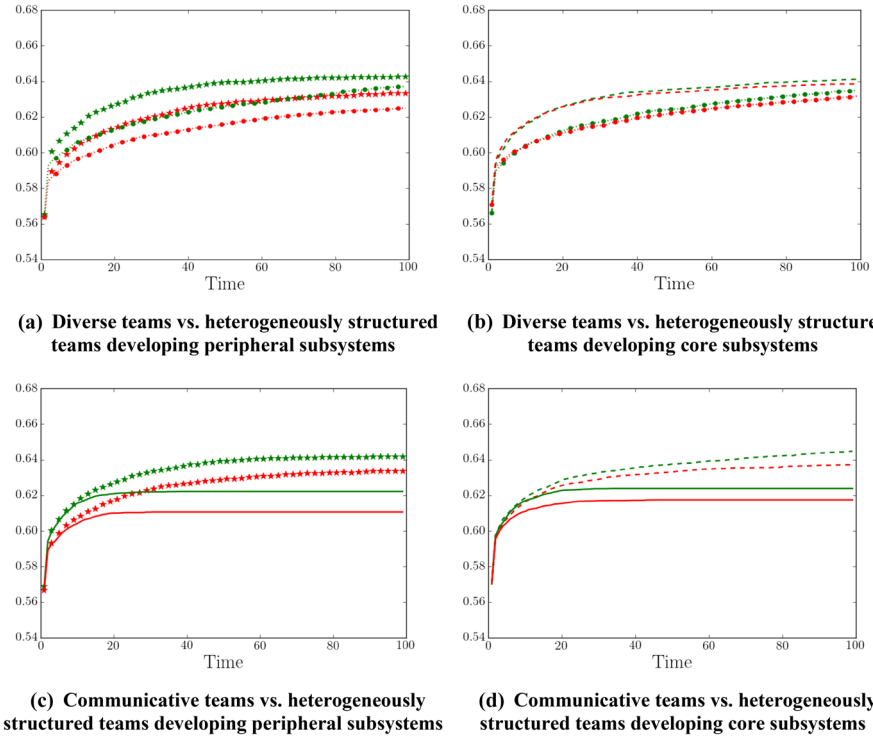
Our results show that the best quality performance is concave in the absorptive capacity level $AC_{q'',q'} = AC \in [0, 1]$, and also, is constant function of the probability by which designers have similar expertise $P(EX_q^j = EX^j) = P(EX_{q'}^j = EX^j) \in [0, 1]$. Similar performance patterns are seen for the average quality performance (see graphs in the Online Appendix). Thus, absorptive capacity level appears to be a highly critical factor in affecting PD performance compared with the distribution of expertise among designers.

4.2 Experiment 2: teams with heterogeneous structures

Managers may use the teams with heterogeneous structures, e.g., some teams with more closely connected structures develop some subsystems, whereas the other subsystems are developed by more diverse teams. In our second set of experiments, we investigate whether teams with heterogeneous structures—which we call heterogeneous teams—result in higher PD performance than that of closely connected/diverse teams. Will PD projects have superior performance if they use teams with heterogeneous structures (i.e., having both diverse and communicative teams)? Does the answer to this question depend on either the interaction pattern among product subsystems or the level of interactions intensity?

We compare the performance of a PD project where diverse teams developing core/peripheral systems with that of the former strategies (i.e., communicative teams or diverse teams). More precisely, we compare the resulting performance of teams with heterogeneous forms (i.e., diverse teams developing core/peripheral systems) with that of teams with uniform structures (i.e., communicative/diverse teams). We define two types of the heterogonous teams: heterogonous core (i.e., diverse teams developing core subsystems and communicative teams developing peripheral subsystems) and heterogonous peripheral (i.e., diverse teams developing peripheral subsystems and communicative teams developing core subsystems). We compare these strategies based on both the best and average quality measures that are defined in Eq. 4 and 5. We simulate each scenario for a fixed number of time periods and record the performance measures of all teams.

As in our second set of experiments, we investigate strategies with heterogeneous forms according to their subsystems' interaction intensity, limiting the experiments with only cyclic and acyclic interaction patterns. In other words, since



(a) Diverse teams vs. heterogeneously structured teams developing peripheral subsystems

(b) Diverse teams vs. heterogeneously structured teams developing core subsystems

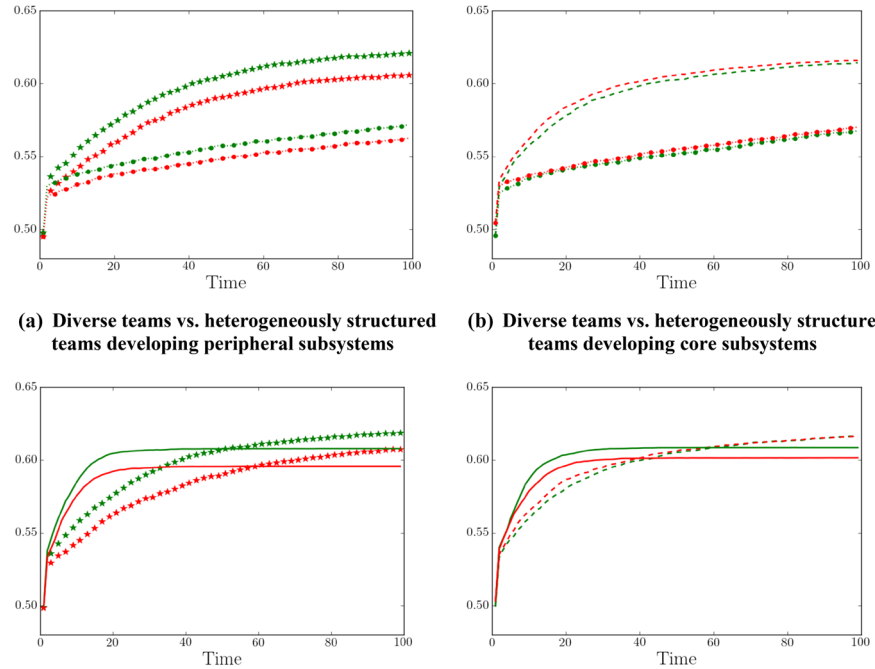
(c) Communicative teams vs. heterogeneously structured teams developing peripheral subsystems

(d) Communicative teams vs. heterogeneously structured teams developing core subsystems

Fig. 6 The best quality performance of PD projects with ($K = 1$ and $C = 1$). *Note* Communicative teams represented by solid and continuous line; diverse teams represented by dotted lines; heterogeneously structured teams developing peripheral represented by asterisks and heterogeneously structured teams developing core subsystems represented by dashes. (Color figure online)

with a modular pattern, to a large extent, teams have a similar interaction intensity, therefore, we drop this pattern in our second set of experiments. Also, for the definition of interaction strength measure, we use $W = 5$ for the weight parameter in Eq. 2 (the value of the weight parameter only helps us to differentiate between teams under different interaction patterns; hence, its value is likely to be trivial as long as teams can have differing interaction intensity levels). With this assumption, and under a subsystems cyclic pattern and $n_b = 5$, the teams' interaction intensities are as follows: $m_1 = 0.8$, $m_2 = 0.8$, $m_3 = 0.6$, $m_4 = 0.4$,$m_5 = 0.2$. However, for a subsystems acyclic pattern and $n_b = 5$, the teams' interaction intensities are as follows: $m_1 = 0.66$, $m_2 = 0.53$, $m_3 = 0.4$, $m_4 = 0.26$, $m_5 = 0.13$.

For each combination (PD setting and subsystems' interaction pattern), we generate 100 landscapes. For each landscape, we create the corresponding PD project scenario (e.g., heterogonous core) and let teams conduct the search process for 100-time periods. This process is repeated for each of the 100 landscapes. The performance at each simulation time is the average performance at that time period across all landscapes.



(a) Diverse teams vs. heterogeneously structured teams developing peripheral subsystems

(b) Diverse teams vs. heterogeneously structured teams developing core subsystems

(c) Communicative teams vs. heterogeneously structured teams developing peripheral subsystems

(d) Communicative teams vs. heterogeneously structured teams developing core subsystems

Fig. 7 The average quality performance of PD projects with ($K = 1$ and $C = 1$). *Note* Communicative teams represented by solid and continuous line; diverse teams represented by dotted lines; heterogeneously structured teams developing peripheral represented by asterisks and heterogeneously structured teams developing core subsystems represented by dashes. (Color figure online)

Graphs in Fig. 6 depict the best quality performance of PD projects (PQ^t in Eq. 4).[8] They show performance of PD projects with $K = 1,\ C = 1$. According to the top panels, heterogeneous teams (i.e., heterogonous core, heterogonous peripheral) result in performance levels higher than or like that of diverse teams. In addition, panels at the bottom indicate that the former set of teams, i.e., with varied forms, tend to achieve higher performance levels than communicative teams. These observations are seen in the other PD projects (e.g., $K = 3,\ C = 1$) that are reported in the Online Appendix. Thus, in PD systems with high integration capability that can attain best quality performance levels, heterogeneous teams are expected to achieve superior best quality solutions than uniformly formed teams, e.g., diverse/communicative teams.

Plots in Fig. 7 indicate that when firms can attain average quality performance, heterogeneous teams have different performance courses, relative to that

[8] For both Figs. 6 and 7, the following setting arrangements have been used. Subsystems interact in modular (blue), cyclical (green), and acyclical (red) patterns. Each point is the average performance of 100 simulation runs, and $n_b = n_q = 5; n_e = 4$.

Table 5 Paired t tests comparing the best quality performance of PD systems with heterogonous core teams with the so-called "X" PD systems

Inputs			Pattern	t value	Pattern	t value
"X" PD systems	*K*	*C*				
Diverse	1	1	Cyclical	3.287*	Acyclical	4.21*
	1	3		− 0.156		1.662
	3	1		1.227		2.803*
	3	3		0.034		1.625
Communicative	1	1		8.925*		11.697 *
	1	3		11.252*		12.507*
	3	1		11.374*		12.795*
	3	3		13.106*		13.676*

Asterisk indicates a 1% significance level

of uniformly formed teams, e.g., diverse/communicative teams. The performance graphs in the top panels show that using heterogeneous teams results in performance levels higher than using diverse teams. In addition, the bottom panels indicate that, in the short run, communicative teams achieve higher performance levels than that of heterogeneous teams. However, in the long run, the latter teams achieve higher performance than the former teams. These observations are seen in the other PD projects (e.g., $K = 3, C = 1$) that are reported in the Online Appendix. Thus, PD systems with low integration capability that can only achieve average quality performance levels, using heterogeneous teams, in the long run, are likely to make superior average quality solutions than when deploying uniformly formed teams. However, in the short run, communicative teams tend to attain higher average quality solutions than heterogeneous teams (e.g., heterogonous core).

To examine the previous performance patterns, we have conducted paired t-tests. Again, as discussed earlier in the previous section, the observations in one sample (e.g., performance of a project with teams whose diversity increases in interaction) can be paired with observations in another sample (e.g., performance of a project with communicative teams). As discussed earlier, we used the average PD performance in the last 10-time periods as a performance measure in our statistical tests. We have conducted four sets of paired t-tests. The null hypothesis for the first set of paired t-tests expects the mean of the best quality of a system with heterogonous core/peripheral systems to be equal to that of a system with diverse teams.[9] Similarly, the second test expects the mean of best quality of the former system to be equal to that of a system with communicative teams.

The results of the first and second paired t-tests are provided in Tables 4 and 5 for PD projects with $n_q = 5$ designers in each team. The results show that heterogeneous teams (e.g., heterogonous core teams) achieve superior design solutions than that of

[9] In other words, the first set of paired t tests, compare PQ^t in Eq. 4 of heterogonous core teams with that of diverse teams. Therefore, positive and negative t values indicate heterogonous core teams are doing, respectively, better and worse than diverse teams.

Table 6 Paired t tests comparing the best quality performance of PD systems with heterogonous peripheral teams with the so-called "X" PD systems

Inputs			Pattern	t value	Pattern	t value
"X" PD systems	K	C				
Diverse	1	1	Cyclical	2.698*	Acyclical	5.083*
	1	3		1.62		2.532
	3	1		– 0.034		4.289*
	3	3		0.491		3.873*
Communicative	1	1		9.852*		12.78 *
	1	3		11.84*		15.586*
	3	1		12.92*		12.629*
	3	3		15.036*		14.591*

Asterisk indicates a 1% significance level

Table 7 Paired t tests comparing the average quality performance of PD systems with heterogonous core teams with the so-called "X" PD systems

Inputs			Pattern	t value	Pattern	t value
"X" PD systems	K	C				
Diverse	1	1	Cyclical	23.934*	Acyclical	31.592*
	1	3		32.815*		25.529*
	3	1		24.05*		35.061*
	3	3		32.018*		27.347*
Communicative	1	1		– 0.826		1.091
	1	3		– 2.296		– 1.572
	3	1		– 1.09		0.737
	3	3		– 3.926*		– 0.871

Note: asterisk indicates a 1% significance level

communicative teams. However, in some PD settings, the best solutions of the former teams do not differ significantly from that of the diverse teams.[10] An example of such settings is a PD project with acyclical subsystems interaction in some settings like $K = 1, C = 2$. These are consistent with the results in Sect. 4.1 where diverse teams are expected to find superior best solutions than communicative teams.

The null hypothesis for the third paired t test expects the mean of average quality of systems with diverse teams developing core/peripheral systems to be equal to that of a system with diverse teams. Analogously, the fourth test expects the mean of average quality of the former systems to be equal to that of a system with communicative teams. For PD projects with $n_b = 7$ designers in each team, these tests

[10] In the results provided in the Online Appendix, we observe somewhat different patterns for $n_b = 7$ designers in each team, and we speculate that this happens as higher number of agents are conducting searches over the landscape, and intuitively, that may shift the overall performance improvement rate of heterogeneous teams in comparison to that of the uniformly formed teams. It is worth noting, our overall insights are independent from these PD setting-related changes in results.

Table 8 Paired t tests comparing the average quality performance of PD systems with heterogonous peripheral teams with the so-called "X" PD systems

Inputs			Pattern	t value	Pattern	t value
"X" PD systems	*K*	*C*				
Diverse	1	1	Cyclical	24.459*	Acyclical	16.743*
	1	3		27.422*		20.899*
	3	1		26.708*		22.105*
	3	3		27.385*		22.327*
Communicative	1	1		– 3.42*		– 5.452*
	1	3		– 1.87		– 7.148*
	3	1		– 2.057		– 6.42*
	3	3		– 3.314*		– 6.838*

Asterisk indicates a 1% significance level

results are presented in Tables 6, 7 and 8. They show that heterogeneous teams (e.g., diverse teams developing core subsystems) achieve higher average quality of solutions than that of diverse teams. However, in some PD settings, the best solutions of the former teams do not differ significantly from that of the communicative teams. An example of such settings is a PD project with acyclical subsystems interaction in some settings like $K = 1,\ C = 2$.

Contemplating all four paired test results, depending on organizational integration capability level, heterogeneous teams may achieve higher performance than teams with uniform structures. When PD systems have high competency in integrating designers' solutions, then heterogeneous teams (e.g., diverse teams developing core) achieve superior design solutions than that of communicative teams. In addition, in PD projects have low integration capability, heterogeneous teams are expected to achieve higher performance than diverse teams. However, those heterogeneous teams may have higher or similar design solutions than that of diverse teams, in PD projects with high integration capability, and that of communicative teams in projects with low integration competency.

In sum, our model expected higher performance levels for projects with heterogeneous teams that utilize both diverse and communicative teams. Those PD projects benefits from superior features of both communicative and diverse teams. Recall that, with uniformly formed communicative teams, when a superior design solution is found, it is quickly and effectively shared among designers. In addition, as discussed earlier, uniformly formed diverse teams utilize a broad collective search effort. Hence, projects that employ heterogeneous teams are likely to have a higher or, at least, similar, performance level to that of uniformly formed teams.

5 Discussion and conclusion

Organizations usually use teams as their means to conduct their PD projects. This paper proposed a model for investigating PD performance consequences of different team assembly strategies. Specifically, according to the social network literature, two

main team structures were studied. In one structure, with a sparse structure, which we refer to as diverse teams, team members interact with designers who mainly do not interact with each other. Alternatively, with a cohesive structure, or what we call communicative teams, designers interact in a densely connected pattern where common-third parties are common.

Generally, in an organizational context, and particularly in the PD area, either of the two team assembly strategies is argued to be associated with distinct performance advantages (Coleman 1990; Obstfeld 2005; Sosa 2011; Burt 2004; Fleming et al. 2007). Although, these general implications can guide PD managers, more research is needed to understand different PD team assembly strategies (Sosa and Marle 2013).

Disentangling the performance effects of product architecture or interaction patterns among subsystems has been a critical topic (MacCormack et al. 2006), and hence, we studied performance effects of team assembly strategies with different product architecture patterns. To that end, we considered three different architectures, modular, cyclical and acyclical, that have been observed empirically (Baldwin and Clark 2000; MacCormack et al. 2006; Baldwin et al. 2014).

We also examined team-formation policies for PD projects with different complexity levels as products can have design spaces with varying complexity levels or interdependencies among their elements (Fleming and Sorenson 2002). Generally, high NPD complexity creates challenges for managers that negatively impact performance such as profit margin (Tatikonda and Rosenthal 2000) and longer PD time (Griffin 1997). Theoretically, also, product complexity affects the relationship between the level of centralization of the product design decisions and product performance (Giannoccaro and Nair 2016). Therefore, in our model, we varied the level of ruggedness of design space to investigate whether team-formation strategies affect PD performance in different ways.

We conceptualized the PD endeavor as collective problem solving. That is designers are simultaneously solving a set of interrelated problems (Thomke 1997). More precisely, each designer conducts either of the following two tasks at a time: (i) locally optimizing his own design task, or (ii) attending design interactions with the other tasks (Mihm et al. 2003).

From a performance perspective, we studied two performance measures to reflect different integration capability of firms. That differentiation between capable and incapable PD systems by using the best and average quality performance measures reflects what teams need to do: integrate knowledge in an ongoing process of mutual adjustment (Kozlowski et al. 1999; Gardner et al. 2012). The knowledge integration, in other words, makes some teams more effective than other teams by developing dynamic capabilities that enable the former teams to integrate knowledge in a systematic and reliable way (Gardner et al. 2012).

Our selection of two performance measures has no conflict with the fact that innovation success usually depends on the quality of the best identified opportunity (Girotra et al. 2010). More specifically, the best and average quality measures that are used in this paper, are built to differentiate PD projects based on their ability to find out the best design solutions which has been discussed both at the team and individual levels (Girotra et al. 2010).

Table 9 Comparing different team-formation strategies

Team formation	Integration capability	Superior strategy
Uniform	High (capable)	Diverse teams
	Low (incapable)	Communicative teams
Heterogeneous-uniform	High (capable)	Heterogeneous > communicative (≥ diverse)
	Low (incapable)	Heterogeneous > diverse (≥ communicative)

In this paper, we relied on simulation to develop a theory (e.g., March 1991; Strang and Macy 2001; and other examples in Harrison et al. 2007). Table 9 provides a summary of our results on the performance of PD teams that are all formed with a uniform strategy. Our results for projects where teams with similar social structures are utilized for all subsystems indicate that depending on the integration capability and costs, managers should use different strategies (the first and second rows of Table 9). If PD systems can efficiently integrate design solutions at low integration costs, diverse teams with high absorptive capacity should be assembled. However, with integration inefficiencies processes, managers should build communicative teams that, according to the average quality measure, tend to find design solutions with higher fitness values than those of the diverse teams.

Our results are in line with previous empirical observations and arguments. Previously, the differing consequences of spare networks with bridging ties and cohesive structures with strong ties are characterized as tension between "the idea problem" versus "the action problem" (Obstfeld 2005; Tiwana 2008). In other words, teams with cohesive structures, are capable of implementing innovative ideas, but are competent to generate ideas. Comparably, diverse teams with a sparse structure have a high capacity to generate innovative ideas but they are deficient in implementing ideas. Such a trade-off has been seen in our results where communicative teams lost the potential to find the best quality solutions, and diverse teams missed the potential to have high average quality performance. In a similar perspective, and based on the creativity and decision-making literature, the designers' social network structure has been argued to affect the NPD front-end process (Khurana and Rosenthal 1998), in which ideas are born and further developed, ending with the go/no-go decision (Kijkuit and Van Den Ende 2007). In particular, diverse-team strategy is expected to improve idea generation, whereas communicative-team formation enhances idea development and evaluation processes. Thus, we suggest the following proposition for future empirical research:

Proposition 1 *If managers consider only a homogenous social structure for the teams* (*developing different subsystems*)*; and integration capability is high* (*low*)*, forming/using diverse* (*communicative*) *teams is advised.*

Managers in PD projects may consider using teams with heterogeneous social structures. Our results in Table 9 provide a simple guideline on when such consideration is expected to result in higher PD performance than strategies that form

teams uniformly (the last two rows of Table 9). If PD systems can efficiently integrate design solutions at low integration costs, then heterogeneous teams attain a superior best design solution than that of communicative teams. However, those variously formed teams are expected to have a superior or similar best design solution as that of diverse teams. When integration processes are afflicted with inefficiencies, teams with heterogeneous social structures achieve higher average design solutions than that of diverse teams. Moreover, the former PD team arrangements attain higher than or similar to, the average design solutions of communicative teams.

In summary, our model expects higher performance levels for PD projects that employ both diverse and communicative teams (see Table 9). This is consistent with the body of research on association of social network features and innovation performance. For instance, Zhou et al. (2009) investigated a high-tech firm in China, and found that too many or too few weak ties [that connect to different social circles and are a source of non-redundant information (Granovetter 1973)] negatively affect creativity, and they suggested an inverted U-relationship between the number of weak ties and creativity. Similarly, studies at the individual level (Schultz and Schreyogg 2013), project level (Tiwana 2008), and firm level (Capaldo 2007) confirm that a combination of weak ties (frequently present in our diverse teams) and strong ties (frequently present in our communicative teams) positively influence innovation performance.

Our results of expected higher performance of the heterogeneous teams, in comparison to that of uniformly formed teams, is also in line with arguments on the small world fostering creativity (Fleming and Marx 2006). The small world structures benefit from both bridging ties and cohesive clusters that facilitate diffusion of new ideas and create more new inventions, which will diffuse more quickly. Similarly, in the organizational context, groups with modest amounts of cross-group linking (i.e., low but nonzero levels) are found associated with higher equilibrium performance levels (Fang et al. 2010). Thus, we provide the following set of propositions for future empirical research:

Proposition 2 *If managers consider both homogenous and heterogenous social structures for the teams* (*developing different subsystems*); *and integration capability is high, forming/using either of the heterogenous and diverse teams is advised.*

Proposition 3 *If managers consider both homogenous and heterogenous social structures for the teams* (*developing different subsystems*); *and integration capability is low, forming/using either of the heterogenous and communicative teams is advised.*

Our work has some implications for the literature on NK landscape search where managerial decision-making problems (e.g., organization design, strategy planning) are conceptualized as problems for which the effective combinations of several interdependent variables should be found (Levinthal 1997; Katila and Ahuja 2002; Billinger et al. 2013). A stream of this research investigates how the

search process features can have significant performance effects for problem solving in complex settings (Fleming 2001; Nickerson and Zenger 2004). Expansion of the search domain (Baumann and Siggelkow 2013), organizational structure (Knudsen and Levinthal 2007; Mihm et al. 2010), and interpersonal organization network (Lazer and Friedman 2007; Fang et al. 2010) are examples of such search process features. We add to this line of research by considering agents' communication effectiveness and expertise distribution in an interpersonal organization network. In particular, we have found that capable organizations should arrange their organizational structure using diverse teams who have high absorptive capacity. Conversely, organizations with high integration inefficiencies, should use communicative, and less diverse teams.

We conclude by discussing some limitations of our work and future research possibilities. First, the NK landscape model imposes some limitations on the number of teams and subsystems that we could include in our experiments, and feature research can validate our results by using alternative models like the recently developed NM landscape models (Buzas and Dinitz 2014; Manukyan et al. 2016) or organizational generalized pay-off functions (Fang et al. 2010; Schilling and Fang 2014), by which large landscape models, e.g., N = 50, 100 can be built.

Second, since a limited number of design elements could have been used in the NK landscape, we used the connected caveman model (Watts 1999) with a fixed structure. However, empirical research has shown that designers' interactions follow scale free properties—with a power of law degree distribution—and, those interactions are not equally distributed among all designers (Braha and Bar-Yam 2004). Hence, a few designers have a large number of interactions, while the other ones have only few relationships.

Lastly, we assumed the PD process is simultaneously executed for all subsystems. However, from a temporal perspective, PD work might be front-loaded (Thomke and Fujimoto 2000), where problems are mainly solved in the early stage. Alternatively, the process can be back-loaded (Fixson and Marion 2012), with a large portion of problems being solved at the later stage of PD process. Investigating whether either of these temporal features affect the performance effects of team-formation strategies can be a promising opportunity for future research.

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