The link between R&D team diversity and innovative performance: A mediated moderation model

Abstract

This paper examines how diversity dimensions, namely gender, skills and education, in R&D teams interact to drive innovation. Our research supports the hypothesis that surface-level diversity might negatively affect R&D team performance when interacting with deep-level diversity. Further, the study considers the mediating effect of social capital to extract value from diverse R&D teams. Social capital favours social interaction by developing harmonious interpersonal relationships among diverse team members. Research hypotheses were tested using the Spanish Technological Innovation Panel (PITEC) for the period 2008-2015. Our mediated-moderation model suggests that high diversity in education or skills in gender diverse teams might adversely affect innovation performance, although the mediating role of R&D social capital diminishes this outcome. This study provides valuable insights for managers aiming to benefit from diversity in R&D teams while minimizing the conflict and mistrust associated with excessive diversity.

Keywords: R&D team diversity; innovation performance; fault line; social capital; mediated moderation model.

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1. Introduction

Research on diversity in innovation teams has revealed ambiguous results regarding the effects of group composition on team performance (for a recent meta-analysis on team diversity refer to Weiss et al. (2018)). One approach emphasizes its positive effect on innovative capacity and breadth of knowledge (Bouncken et al., 2016; Garcia Martinez et al., 2017) since diverse teams are characterized by a wide-ranging store of learning and expertise (Bowers et al., 2000). Although heterogeneous teams are able to tap into a wider range of information sources and generate alternative and unique viewpoints, diversity can inhibit communication and coordination among team members and lead to group fragmentation and subgroup rivalry, which affects team performance (Smith and Hou, 2015). Strong subgroups often reduce interpersonal attraction, psychological commitment, intergroup connections, and group consistency (Smith et al., 1994; Tsui et al., 1992), and this, in turn, promotes behavioural disintegration (Georgakakis et al., 2017). The existence of group faultlines produced by excessive dimensions of diversity has been thoroughly examined in the literature since Lau and Murnighan's (1998) seminal paper. However, most research to date has focused on the performance implications of different dimensions of diversity in isolation (Gratton et al., 2007; Thatcher et al., 2003; van Knippenberg et al., 2010) and has not accounted for the interaction effects between diversity dimensions.

This study aims to address this research gap by differentiating among types of diversity, namely gender, skills, and education diversity – facets of surface and deep level diversity, and investigating how they interact to drive innovation. Also, it responds to calls for a more holistic view of the overall potential influence of different facets of diversity (Shore et al., 2009). Further, we examine how social capital may mediate the relationships between the interaction between diversity facets and innovation performance. The present study is based on a measure of social capital used by Garcia Martinez et al. (2019) which considers two dimensions of social capital, namely structural capital and relational capital. Prior research (e.g., Fonti and Maoret, 2016) argues that superior firm performance is not only related to diversity in the composition of their teams (i.e., educational level and occupational background) but also to their stock of social capital which promotes more harmonious interpersonal relationships among diverse members. Scholarly efforts to understand the complexities surrounding the effect of team diversity on innovation outcomes (Horwitz and Horwitz, 2007) have, however, left a gap in our understanding of how firms manage high levels of diversity within R&D teams which require interactions among team members and trusted communication (Garcia Martinez et al., 2017) to improve team functioning. In this regard, our study provides a valuable breakthrough on how social capital may enable some benefits from diversity while mitigating its potential downsides.

Studying surface and deep-level diversity, this study seeks to contribute to diversity research in two ways. First, the potential effects of diversity on firm innovative performance are being examined in a growing body of empirical studies (Brettel et al., 2011; Hoegl and Proserpio, 2004; Keller, 2001). Only a few studies in the literature have considered several diversity attributes present simultaneously in innovation teams and not just in isolation (e.g., Iseke et al. 2015; Garcia Martinez et al. 2017). In this study, we consider the effects of having a social categorically diverse yet informational heterogeneous R&D teams on innovation performance.

Second, this study contributes to diversity research by proposing and testing the mediating role of social capital in the interactive effects of different diversity dimensions (i.e., surface-level and deep-level diversity) on innovation performance. Social capital, such as closeness and trusting relationships among employees, helps firms to manage intensive communication (Nielsen and Nielsen, 2009). Experience and skill sharing among team members impede the creation of faultlines when there is excessive diversity.

The remainder of this paper is organized as follows. The next section provides the literature review and hypotheses. It is followed by the data analysis, research methodology, and the results of the empirical analysis. Finally, theoretical contributions, managerial implications, limitations, and future research suggestions are outlined.

2. Conceptual framework and development of hypotheses

2.1 Diversity interaction effects

Team diversity refers to the differences among individual members of a team that can exist based on shared characteristics that lead to the perception that the other is different from oneself (Harrison and Klein, 2007, Jackson et al., 1995, Dayan et al., 2017). Research on team diversity has distinguished between two types of diversity dimensions. First, deep-level diversity refers to the differences between team members' psychological features, including cognitive talent, thoughts, values, expertise, and aptitude (Harrison et al., 2002). Second, surface-level diversity refers to the differences between team members based on obvious demographic attributes. An individual differentiates himself or herself from others with regard to detectable or observable attributes such as sex, age, and ethnicity (Edmondson and Harvey, 2017; Harrison et al., 2002).

While a number of recent studies outline that some facets of deep-level diversity, such as education and skills, increase the group's creativity and innovation (Faems and Subramanian, 2013; Garcia Martinez et al., 2017), the diversity literature reports conflicting evidence regarding the relationship between surface-level diversity dimensions (e.g., gender) and performance outcomes. On one hand, drawing from a combination of social categorization theory (Tajfel, 1981), social identity theory (Turner et al., 1987), and the similarity-attraction paradigm (Byrne, 1971), this perspective suggests that differences in demographic characteristics among team members may split a group into subgroups based on one or more demographic attributes (Lau and Murnighan, 2005), and therefore a strong "fault line" is present. This can lead to conflict and hinder team cohesion and commitment (Faems and Subramanian, 2013; Jackson et al., 1991), thus reducing efficiency (Østergaard et al., 2011).

On the other hand, a cognitive resource perspective suggests that diversity can have a positive impact on group performance since members can access a wide range of viewpoints, knowledge, and skills (Gruenfeld et al., 1996). Although this perspective has been mainly related to information diversity due to the interchange of divergent views and tasks (Jehn, 1997), we contend that facets of diversity usually characterized as social category diversity, such as gender, may also be associated with task-related conflicts and elicit a positive effect. Hence, we argue that the nature of tasks performed by R&D teams provides a setting where demographic faultlines can be a 'healthy divide' (Gibson and Vermeulen, 2003). A number of studies find that gender-diverse workforces innovate better and thus achieve higher output and returns (Díaz-García et al., 2013; Fernandez Sastre, 2015; Garcia Martinez et al., 2017; Østergaard et al., 2011)(Xie et al., 2020). These results have often been explained by the existence of different thinking styles and behavioural modes that can complement each other and increase information availability, perspectives, skills, and knowledge (García Martínez et al., 2017).

Hence, diversity could be a 'double-edged sword' (Horwitz and Horwitz, 2007) for its contradictory influence on organizational outcomes. To fully understand this process, there is a need for research to simultaneously examine several of the dimensions of diversity that characterize teams' interactions (Weiss et al., 2018). The central premise of alignment theories is that multiple characteristics of individual differences are likely to be salient at the same time, and their influence must therefore be considered simultaneously (Bezrukova et al., 2007). In this paper, we consider the effects of having social categorically diverse yet informational heterogeneous R&D teams on innovation performance. Increasing team diversity dimensions increases the need for interaction, communication, and coordination within the firm, leading to possible conflict and distrust (Goodstein et al., 1994). Compared to homogenous groups, diverse teams are found to have less cohesiveness (Harrison et al., 1998), more conflict and more misunderstanding (Jehn, 1997), less cooperation (Chatman and Flynn, 2001), and more dissatisfaction (Østergaard et al., 2011) as well as increased turnover (Jackson et al., 1991). Therefore, having broad team diversity will lead to more task conflicts, lower diffusion of the information between employees and lower team cohesion(Goodstein et al., 1994; Jehn, 1997), which can decrease a firm´s propensity to innovate. Therefore, we hypothesise the following:

Hypothesis 1. Skill diversity negatively moderates the relationship between R&D team members' gender diversity and innovative performance. The positive association between gender diversity and innovative performance decreases as skills diversity increases.

Hypothesis 2. Education diversity negatively moderates the relationship between R&D team members' gender diversity and innovative performance. The positive association between gender diversity and innovative performance decreases as education diversity increases.

2.2 The mediating effect of social capital

Social capital is defined as "the aggregate of resources embedded within, available through, and derived from the network of relationships possessed by an individual or organization" (Inkpen and Tsang, 2005, p. 151). Recent work has claimed that the acquisition and accumulation of intangible resources such as social capital can support the implementation of an organization's competitive strategy (Subramony et al., 2018). Social capital as an important intangible asset incorporates features of social interaction—such as norms, trust and values (Yan and Guan, 2018) —and stable task relationships among employees, thus leading to better organizational performance (Fonti and Maoret, 2016). According to the literature, three dimensions of social capital can be considered: relational, structural, and cognitive (Nahapiet and Ghoshal, 1998). Relational capital indicates the strength and quality of relationships with others such as trust, respect, and even friendship; structural capital denotes the general pattern of connections between partners; and cognitive capital means the resources developed by an individual in sharing expertise and experience (Yan and Guan, 2018).

In spite of the relevance of social capital in innovation (Nahapiet and Ghoshal, 1998), there is no consensus among scholars about the relationship between social capital and human capital in relation to innovation. Indeed, the existing research has argued that human capital and social capital are complementary, intangible resources that are critical for organizational performance (Subramony et al., 2018). Social capital encased in strong ties helps to increase cohesion, enhance mutual trust between all members of the team, and improve the team members' ability to pursue specific goals (Fonti and Maoret, 2016). Harrison et al. (2002) demonstrated that as team members spend more time collaborating, the undesirable impact of surface-level diversity on team cohesiveness is diminished. In the same vein, Tekleab et al. (2016)

suggested that increased close interaction and intergroup cooperation reduces "dysfunctional" conflict while also improving interpersonal relationships and the level of cohesion between diverse team members. Evans and Carson (2005) also highlighted the fact that social integration (i.e., structural capital) and trust and support (i.e., relational capital) are critical for group performance because they overcome the negative impacts of many types of diversity.

Extending this line of research, we propose that social capital, emerging from stable relational ties between employees (Fonti and Maoret, 2016), can mediate the interactive effects of different diversity dimensions (i.e., surface-level and deep-level diversity) on innovation performance. This is because teams with high levels of social capital display great accord in their communication as well as integration and information interchanges, which influences innovation activities. Social capital might facilitate the "deployment" of human capital through stable ties, and in turn this helps the team to work together more efficiently and effectively (Fonti and Maoret, 2016). Based on the preceding discussion, we argue that social capital based on interaction among team members and trusted communication flows can help to leverage the positive effects of R&D team diversity on firms' innovative performance.

Hypothesis 3a: Social capital mediates the negative moderating effect of skills diversity on the relationship between R&D team members' gender diversity and innovation performance.

Hypothesis 3b. Social capital mediates the negative moderating effect of education diversity on the relationship between R&D team members' gender diversity and innovation performance.

The model of our hypotheses is illustrated in Figure 1.

Insert Figure 1 about here

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3. Methodology

3.1 Data and sample

The data source is the Technological Innovation Panel (PITEC), which is a statistical tool for analysing the innovation activities of Spanish companies over time. The data[1] are collected through a collaboration between different organizations, the Spanish National Statistics Institute (INE), the Spanish Science and Technology Foundation (FECYT) and the Foundation for Technological Innovation (COTEC). The PITEC dataset includes data on about 12,000 firms going back to 2003 and offers advantages in the study of diversity in R&D teams when

[1] The database is placed at the disposal of researchers on the FECYT site: http://icono.fecyt.es/contenido.asp?dir=05%29Publi/AA%29panel

compared to the Community Innovation Survey (CIS) (For instance, CIS 2012 and 2014 covered only the percentage of enterprise's employees with a tertiary level of educational attainment). Furthermore, it includes exhaustive information on firms' R&D activities and different classifications of R&D staff in terms of gender, education and functional field, which are all very important variables in diversity research. PITEC is a panel data survey, and so it enables us to alleviate several of the estimation problems faced by previous innovation studies that used the CIS dataset, such as the simultaneity between innovation inputs and outputs, by lagging the independent variables (Mairesse and Mohnen, 2010). Using lagged variables allows us to reduce the problems of common method bias, because the temporal precedence of the predictor variables is firmly known before the outcomes are observed (Podsakoff et al., 2003). In this study, the focus is on manufacturing firms across 24 industries, and it is based on the Spanish National Classification of Economic Activity (CNAE-2009) that carried out internal R&D activities over the period 2008–2015. Our final sample includes 30,999 observations.

3.2 Measures

3.2.1. Dependent variables

Product innovation relates to the introduction of a good or service that is new or significantly improved in terms of its technical characteristics or other functionalities or uses. We introduce a binary variable showing whether or not a firm introduced a product innovation during last three years (Crescenzi and Gagliardi, 2018). *Process innovation* is the implementation of new or significantly improved production or distribution methods. Similarly, we create a dummy variable showing whether a firm introduced any new or significantly improved processes for producing goods or services over the study period (Lee et al., 2017; Tsinopoulos et al., 2018).

3.2.2. Dependent variables

R&D team diversity is well-defined as the distribution of divergences among R&D team members with respect to a common characteristic. We use Blau's (1977) index of heterogeneity:

$$D = 1 - \sum_{i=1}^{k} p_i^2 \qquad (1)$$

where k denotes the whole number of categories of a variable, and p_i is the proportion of R&D team members who fall within category k. The lowest value, which is zero, is obtained when all members of the group belong to the same category and there is no variability (e.g., all R&D team members are male). The diversity index is higher when the characteristics are widely distributed across categories. Thus, the operational maximum is achieved if the group members are equally distributed over all the categories (i.e., $p_1 = p_2 = \ldots = p_k$). Nevertheless, the operational maximum is limited by the number of categories k (equation 2):

$$\text{Operational min and operational max} = 0 \text{ and } \frac{k-1}{k} \quad (2)$$

In order to avert potential bias due to different numbers of categories of the diversity variables, we normalize our diversity indices over an interval of 0 to 1 by dividing them by their respective operational maximums (equation 3):

$$\text{Standardized Diversity Index} = \frac{(1)}{(2)} \qquad (3)$$

Surface-level diversity refers to demographic attributes such as age, race or gender. The PITEC database permits the use of a demographic attribute, gender. In our study, *gender* is a binary variable, and Blau's gender diversity index can range from zero (when there is only one gender represented in the R&D team) to 0.50 (when there is an equal number of men and women in the R&D team). Regarding deep-level diversity, two measures are used in this study. First, *skills* diversity is categorized based on three different occupational tasks related to the experience of the R&D team members: 1) researchers, 2) technicians, and 3) supporting staff. Blau's index for skill diversity can vary from zero (when there is a single skill area represented in the R&D team) to 0.66 (when there are the same number of R&D members in all three skill areas). The second measure is *education* diversity, which includes four categories: 1) PhD, 2) bachelor's degree, 3) secondary education, and 4) other studies (i.e., vocational training, etc.). In this case, Blau's index ranges from zero (when all R&D team members fall within the same educational level) to 0.75 (when there are equal numbers of R&D team members across all educational levels). Table 1 shows the main characteristics of the firms' samples.

3.3 Mediating variable

R&D social capital is operationalized using two dimensions, namely structural capital and relational capital (Garcia Martinez et al., 2019). In the case of structural capital, we use managerial flexibility, measured by the introduction of new business practices in management and work procedures, such as learning, training programs, participation in decision making and sharing knowledge (Sánchez et al., 2014). These practices enable firms to manage intensive communication and tacit knowledge exchanges between different team members (Nielsen and Nielsen, 2009) and therefore diminish the inherently dysfunctional nature of functional diversity (Evans and Carson, 2005).

Regarding relational capital, we measure the introduction of new ways to manage external relationships with other companies or public institutions. Firms with high levels of structural social capital are able to easily combine and exchange information with other teams' members to achieve superior innovation performance (Mazzucchelli et al., 2019). De Propis (2002) has postulated that superior firm innovative performance is positively related to inter-firm co-operation and networking. The co-sharing of information and resources channelled through these inter-firm linkages could provide firms with the capability to overcome internal shortcomings. Studies of firm-level innovation processes using the Community Innovation Surveys (CIS) (Giovannetti and Piga 2017) have argued that knowledge transferred through active and passive cooperation increases innovation output. Indeed, Freel and Harrison (2006) used a larger regional survey of over 1300 small and medium sized manufacturing and service sector firms in Northern England and Scotland and found a positive association between firm-level innovation success and cooperation with a variety of potential network partners.

The variable "R&D social capital" is a count variable that captures the number of changes in organisational capabilities relating to management and procedures and external relationships that a firm uses, and it therefore varies between a value of 0 if firms had not introduced any changes and a value of 2 if the maximum number of changes were adopted.

3.4 Control variables

Firm size: This is measured by (the natural logarithm of) the number of employees (Damanpour, 1991). The natural logarithm is used to reduce the skewness of the distribution (Dul and Ceylan, 2014). In addition, we account for the non-linear effects of size by calculating the square of the size (*Firm SizeSq*).

R&D team size: This is measured by (the natural logarithm of) the number of full-time employees in the R&D department. Again, we take the non-linear effect of the size of the R&D team into account by calculating the square of the number of members of the R&D team (*R&D Team SizeSq*).

Innovation intensity: This is determined as innovation expenditure as a share of sales. Innovation expenditure comprises internal and external R&D, training for innovation, acquisition of machinery and knowledge for innovation, and preparation of the market for the introduction of innovations (De Faria et al., 2010). We also take innovation intensity as a squared term to control for a non-linear relationship between innovation expenditure and a firm's innovative performance.

Technology intensity: In order to control for industry affiliation, we follow the OECD classification of industries in terms of technology intensity (OCDE, 2005). We generate four industry dummies to classify manufacturing firms into four categories: high, medium-high, medium-low, and low-tech industry. We use high-tech industry as the baseline for the models.

Year effects: This study uses firm-level innovation performance data from 2008 to 2015. Dummy variables for eight years are used to control for unobserved factors that vary over time but are relatively invariant across industries. Table A.1 in Appendix A summarizes the variable names, uses, and definitions.

Insert Table 1 here

3.5 Research design

We use a Generalized Structural Equation Model (GSEM) (Stata 14 gsem command) to analyse the data. This model allows a logit specification for our dependent variables and provides a means for testing simultaneous equations and mediated moderation effects with bootstrapping (Wood et al., 2015).

Our analysis follows the approach suggested by Preacher and Hayes (2004) and Muller and Judd (2005) for mediated moderation using simultaneous path models. Mediated moderation models involve exploring mediating mechanisms to explain an overall interaction between an independent variable and a moderating variable in predicting a dependent variable (Fairchild et al., 2009). This means that the interaction effect of the independent variable (gender diversity) and moderator variables (education diversity and skills diversity) on the dependent variables (product innovation and process innovation) is mediated through the mediator variable (social capital). A prerequisite of a mediated moderation model is the occurrence of overall moderation between the independent and dependent variables to explain whether the mediating process accounts for this moderation.

To test the interaction effects between the diversity facets (H1 and H2), we follow established methods (Aiken and West, 1991) to mean-centre the predictor and moderator variables before creating the interaction terms and then plot the interaction effect. To test the mediation hypotheses (H3a and H3b), which postulate a mediation effect of social capital on the impact of the interaction of diversity facets on innovation performance, we follow the methodology proposed by Baron and Kenny (1986).

In line with this procedure, we estimate three regression models for each moderating variable: education diversity and skills diversity:

$$Y= a_1X+ b_1Mo+ c_1X*Mo \quad (4)$$

$$Me= a_2X+ b_2Mo+ c_2X*Mo \quad (5)$$

$$Y= a_3X+ b_3Mo+ c_3X*Mo+ d_3Me+ e_3Me*Mo \quad (6)$$

where X is the independent variable (gender diversity), Mo is the moderator variable (education diversity and skills diversity), Me is the mediator variable (social capital), and Y is the dependent variable (product innovation and process innovations).

According to Muller and Judd (2005), three conditions should be met to support a mediated moderation effect. The moderation between independent variable - gender diversity (X) and moderator - education diversity and skills diversity (Mo) must occur, that is, c_1 in equation 4 must be statistically significant. If it is, the term of interaction (c_2) between the independent variable -gender diversity and moderator- education and skills diversity (Mo) in its effect on dependent variable – innovation performance (Y) must be reduced in magnitude or even insignificant (in case of full mediated moderation), that is, c_3 in equation 6 should be smaller in absolute value than c_1 in Equation 4 when the mediator- social capital (Me) and the Me*Mo interaction term are added into the model. Third, at least one of the following conditions must be present, either both the interaction term between the independent variable (X) and the moderator (Mo) in its effect on the mediator (social capital) (i.e., c_2 must be significant in equation 5), and the direct effect of the mediator (Me) on the dependent variable (Y) in equation 6 must be significant (i.e., d_3 must be significant), or both the effect of the independent variable on the mediator (i.e., a_2 is significant in equation 5) and the interaction term between the mediator and the moderator in its effect on the dependent variable in equation 6 must be significant (i.e., e_3 is nonzero).

We also check the robustness of our models using bootstrapping confidence intervals at the mean and +/-1 SD of the moderator to determine the statistical significance of the indirect effect of social capital.

4. Results

Table 2 provides descriptive statistics and correlations of the variables included in the study. The highest correlation is 0.60, thereby suggesting low multicollinearity risks (Tsui et al., 1995). This is confirmed by the analysis of the Variance of Inflation (Vif) (Wooldridge, 2002). The maximum Vif value is 1.53, well below the rule of thumb cut-off of 10, which again indicates that there are no serious multicollinearity problems in the models (Neter et al., 1996).

Insert Table 2 about here

4.1 Diversity interaction effects

Tables 3 and 4 provide an overview of the results. The diversity variables (gender, skills, and education) are positively associated with product and process innovations. Hypothesis 1 posits that skills diversity negatively moderates the relationship between gender diversity and innovative performance. Models 3 and 7 (Tables 3 and 4) show that gender diversity in R&D teams is significantly and positively related to innovation performance (product innovation: $\beta = 1.188$, $p < 0.001$; process innovation $\beta = .935$, $p < 0.001$). However, the interaction term for *gender diversity X skills diversity* is negative and significant for both product innovation (Model 5 in Table 3: $\beta = -.736$, $p < 0.001$) and process innovations (Model 9 in Table 4: $\beta = -.712$, $p < 0.001$). A simple slope analysis (Aiken and West, 1991) shows that gender diversity is positively related to product ($\beta = 0.656$, $p < 0.001$; Figure 2a) and process innovation ($\beta = 0.571$, $p < 0.001$; Figure 2b) at low levels of R&D team skills diversity. By contrast, at high levels of skills diversity, the relationship between gender diversity and product innovation is less positive ($\beta = 0.237$, $p < 0.05$). Interestingly, the effect of gender diversity on process innovation is not significant ($\beta = 0.164$, *ns*) at high levels of skills diversity. These results are consistent with H1 which states that skills diversity weakens the positive effect of gender diversity on firms' innovative performance.

Hypothesis 2 states that education diversity negatively moderates the relationship between gender diversity and innovative performance. The interaction term for *gender X education diversity* is also significantly negative for both product innovation (Model 3 in Table 3: $\beta = -1.836$, $p < 0.001$) and process innovation (Model 7 in Table 4: $\beta = -1.413$, $p < 0.001$). Figure 3 shows that the positive effect of gender diversity on innovation performance disappears when education diversity increases. At low levels of education diversity, the relationship between gender diversity and product innovation ($\beta= 0.124$, $p < 0.001$; Figure 3 a) and process innovation ($\beta = 0.975$, $p < 0.01$; Figure 3b) is positive, whereas at high levels of education diversity, the relationship between gender diversity and both product innovation ($\beta = -0.05$, *ns*) and process innovation ($\beta = -0.017$, *ns*) is no longer significant, thereby supporting H2.

Taken together, the findings suggest that increasing levels of R&D team diversity can lead to conflict and distrust (Ancona and Caldwell, 1992). This is because heterogeneous R&D teams tend to fragment into homogenous subgroups, creating social barriers and constituting a principal impediment to group cohesion.

Insert Table 3 and 4 about here

Insert Figure 2 and 3 about here

4.2 The mediating effect of social capital

H3a proposes that social capital mediates the negative moderating effect of skills diversity on the relationship between gender diversity and innovation performance. Model 2 (Tables 3 and 4) indicates that gender diversity is positively related to social capital (β = 0.099, $p <$ 0.001). In addition, the interaction of gender diversity and skills diversity has a negative effect on social capital (β = -0.137, $p <$ 0.05). Therefore, the results meet the second requirement of mediated moderation analysis. In order to test the third step of mediated moderation analysis, the mediating variable - *social capital* and the interaction terms between social capital and skills diversity are added to Model 6 (Table 3) and Model 10 (Table 4). The results show that the interaction of *gender diversity X skills diversity* on product innovation (Model 6: β = -0.612 $p <$ 0.01) and process innovation (Model 10: β = -0.664, $p <$ 0.05) becomes smaller in absolute value than the coefficients in Model 5 (β =-0.736, $p <$ 0.001 for product innovation) and Model 9 (β = -0.712, $p <$ 0.001 for process innovation). Hence, these results meet the third condition for mediated moderation, suggesting that social capital partially mediates the interaction between skills diversity and gender diversity on innovative performance. Therefore, H3a is supported.

Regarding H3b, Model 1 (Tables 3 and 4) shows that *gender diversity* (β = 0.149, $p <$ 0.001) and the interaction term for *gender diversity X education diversity* are significant for social capital (β = -0.212, $p <$ 0.001). Models 4 and 8 meet the third requirement of mediated moderation analysis, that is, the coefficients of social capital and the interaction terms between *education diversity X social capital* are significant for both product and process innovation. Moreover, Models 4 and 8 show that when the mediator - *social capital* and its interaction terms with education diversity are added, the coefficients of *gender diversity X* *education* diversity remain statistically significant but become somewhat smaller in absolute value (β = -1.639, $p < 0.001$ for product innovation; β = -1.288, $p < 0.01$ for process innovation) compared to Model 3 (β = -1.826, $p < 0.001$ for product innovation) and Model 7 (β = -1.413, $p < 0.001$ for process innovation). These results support H3b, suggesting that social capital mediates the negative moderating effect of education diversity on the relationship between gender diversity and innovation performance.

In order to help with the interpretation, we calculate the simple effects of social capital on product and process innovations at both low and high levels of both moderating variables (education diversity and skills diversity). The results in Table 5 suggest that the mediating role of social capital in explaining product and process innovations for both high and low levels of education and skills diversity.

Insert Table 5 about here

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5. Discussion and conclusions

This research explores how diversity dimensions in R&D teams interact to drive innovation. Diverse teams are essential to organizational innovation, creativity, and productivity (Bouncken et al., 2016). However, too much diversity can reduce innovation teams' performance by negatively affecting cohesion, decision-making quality, and members' commitment to the group (Tsui et al., 1992; Smith et al, 1994; Blau, 1977).

Additionally, we consider the mediating role of social capital in leveraging diversity as a strategic resource for innovation. Consistent with upper-echelon diversity studies (Garcia Martinez et al., 2017; Horwitz and Horwitz, 2007) we find evidence of the double-edged nature of diversity suggesting that diversity in R&D teams is not always a source of potential benefits, because the formation of strong subgroups within R&D teams could emerge. As subgroups grow within R&D teams, group effectiveness is undermined, and therefore team performance suffers. To better understand the effects of a group's demographic differences on firm performance, Ndofor et al. (2015) indicated the importance of investigating the joint effects of multiple diversity characteristics and their interrelationships, rather than a single characteristic of an individual. Our moderation results suggest that functional heterogeneity (education and skills diversity) and demographic heterogeneity (gender diversity) interact negatively, reducing innovation performance. These findings support the social categorization perspective (King et al., 2009), which suggests that differences between members aggravate problems in interpersonal relationships and increase emotional conflicts when executing tasks, which will potentially disrupt team functioning. An abundance of studies on diversity has provided evidence for the disruptive effect of fault lines, including task conflict, job stress, lack of group cohesiveness, and decreased levels of satisfaction, which make teamwork among group members more difficult (Gibson and Vermeulen, 2003; Lau and Murnighan, 2005; Østergaard et al., 2011). Career backgrounds (i.e., education and skills diversity) lead to the fragmentation of cognitively diverse R&D teams into homogenous subgroups, producing functional disruptions in innovation processes and affecting group performance (Geogakakis et al., 2017). Excessive diversity can create a bottleneck in the dissemination of information by hampering creative decision making, which affects team performance (Auh and Menguc, 2005). Blau (1977) depicted the tendency to identify with similar others rather than members of the larger group as the most destructive force affecting groups and organizations because homogenous subgroups create social barriers, heighten the potential for conflict, and constitute the principal impediments to group cohesion (Lau and Murnighan, 2005; O'Leary and Mortensen, 2010). In the same way, prior research has shown that heterogeneous groups experience more difficulties than homogenous groups in defining how to move forward with a task (Jehn, 1997; Watson et al., 1993).

Second, this study emphasizes the importance of social capital in decreasing the negative effect of excessive diversity. Social capital mediates the interaction effects between different types of diversity and innovation performance. In other words, diverse teams that exhibit higher levels of social capital are more effective in appreciating the differences that others bring to the team, which in turn facilitates the coordination of dispersed activities (Fonti and Maoret, 2016), leading to enhanced innovation performance. Social capital reduces the fragmentation effect of higher diversity and extracts potential benefits from multiple knowledge subgroups. Fonti and Maoret (2016) suggested that social capital might indirectly affect organizational performance by aiding in the full deployment of human capital within the organization. The same authors showed how relational stability between employees unlocks the value of human capital, allowing better leverage of the skills and experiences of these individuals. Social capital can reduce functional task conflict, enhance team communication, and promote the overlapping knowledge and expertise that are needed for strong innovation performance (Fonti and Maoret, 2016). Having good relationships among group members can reduce the impacts of their backgrounds and demographic differences and can make teamwork and communication among the group members less difficult (Evans and Carson, 2005). In our study, social capital acts as an internal mechanism in mitigation by reducing the negative consequences of the fault lines. Evans and Carson (2005) concluded that social capital, which is generally considered an asset embedded in social relationships, offers positive facets that may alleviate the difficulties posed by functionally diverse teams.

5.1 Contributions and managerial implications

Our study provides managers with helpful insights into how diversity can be used as a strategic resource to foster innovativeness. The practical relevance of our study comes from the fact that the configuration of the R&D team is under the oversight of the firm, that is, firms have the flexibility and freedom to encourage or minimize diversity (Auh and Menguc, 2005). Managers should be aware of the structure and the complexities of the various teams they create within the organization. Excessive diversity in a team will make it split up into subgroups that might find it difficult to cooperate with each other or might even compete (Rico et al., 2007), and this leads to emotional conflict, which can be counterproductive (Barkema and Shvyrkov, 2007). This study points out the complexities of team diversity and the need to invest in social capital to ensure team cohesion and create better firm performance. To overcome the knowledge fragmentation arising from the presence of strong faultlines, managers should understand the importance of cultivating strong social relationships and collaboration among team members to foster knowledge exchange and integration, thereby improving team innovativeness. Social capital, such as close and trusting relationships among the members of the organization, may improve the functioning of diverse teams that have strong faultlines. Interpersonal trust between organizational members reinforces the processing of the tacit knowledge needed to achieve high levels of task interdependence and to avoid the conflict and mistrust associated with diversity (Tekleab et al., 2016).

5.2 Limitations and future research

This study has several limitations. First, this paper examines how diversity dimensions, namely gender, skills and education, in R&D teams interact to drive innovation. Future diversity studies could focus on a deeper analysis within firms, beyond R&D teams, and consider other types of diversity, such as age and race, and deeper characteristics, such as experience and personality, to unpack the effects of diversity on firm performance further. Second, we use data exclusively from Spain. Evidence from other countries on the differential impacts of diversity dimensions on innovation performance might help to develop more general empirical evidence. A promising future research direction is to consider the influence of country-specific dimensions, whether cultural or institutional, on innovation performance, by means of cross-country studies. Recent studies highlight the importance of cultural dimensions in innovation (Efrat, 2014). Finally, in this paper we focus only on structural and rational social capital; future research could consider more dimensions of social capital. In particular, we suggest including team-bridging and team-bonding because these aspects have been found to play important roles in integrating diversified knowledge activities among diverse teams (Han et al., 2014).

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Appendix 1 - Table A.1. Variables' Description

Variables	Type	Definitions
Dependent Variables		
Product Innovation	Binary	Dummy variable taking value 1 if the firm introduced product innovation
Process Innovation	Binary	Dummy variable taking value 1 if the firm introduced process innovation
Independent Variables		
Gender diversity	Categorical	0= male; 1=female
Skills diversity	Categorical	1 = researchers; 2 = technicians; 3= supporting staff
Education diversity	Categorical	1 = PhD; 2= Bachelor, 3= Secondary education; 4= other studies
Mediating variable		
Social capital	Continuous	Number of changes in organisational capabilities relating to management and procedures and external relationships.
Control variables		
Firm Size	Log	Number of employees at the firm (Ln)
Firm SizeSq	Log	Number of employees (Ln) squared
R&D Team Size	Log	Number of full-time employees in the R&D department (Ln)
R&D Team SizeSq	Log	Number of full-time employees in the R&D department (Ln) squared
Innovation Intensity	Share	Total expenditure on innovation activities as a percentage of total turnover
Innovation IntensitySq	Share	Innovation intensity squared
High-tech firm	Binary	One, if the firm belongs to NACE 353, 2423, 30, 32, 33
Medium-high tech firm	Binary	One, if the firm belongs to NACE 31, 34, 24 (excl. 2423), 352+359, 29
Medium-low tech firm	Binary	One, if the firm belongs to NACE 351, 25, 23, 26, 27-28
Low-tech firm	Binary	One, if the firm belongs to NACE 36-37, 20-22, 15-16, 17-19
Year dummies	Binary	Dummy variables indicating the year to which observations belong to (2008-2015)

Table 1. Samples descriptive statistics

Variables	Characteristics	Percent %
Gender	Male	69.4
	Female	30.6
Education	PhD	7.5
	Bachelor	48.9
	Secondary education	20.5
	Other studies	23.1
Skills	Researchers	49.5
	Technicians	36
	Supporting staff	14.5
Number of employees (size)	Less than 50	51.5
	Between 50-99	15.6
	Between 100-449	23.9
	500 or more	9
R&D team size	Less than 5 members	60.4
	Between 5-19 members	27.6
	Between 20-39 members	6.5
	40 or more	5.5

Table 2. Means, standard deviations and correlation coefficients

Variables	Mean	S.D	1	2	3	4	5	6	7	8	9
1. Product innovation	0.62	0.62	1								
2. Process innovation	0.58	0.49	0.29*	1							
3.Gender	0.30	0.38	0.27*	0.20*	1						
4.Education	0.36	0.36	0.34*	0.25*	0.55*	1					
5.Skills	0.32	0.28	0.22*	0.14*	0.32*	0.47*	1				
6. Firm Size	4.08	1.36	0.18*	0.24*	0.29*	0.32*	0.20*	1			
7. Inn. intensity	0.05	0.41	0.03*	0.01	0.04*	0.04*	0.01	-0.08*	1		
8. R&D team Size	1.71	1.04	0.36*	0.26*	0.50*	0.60*	0.35*	0.51*	0.05*	1	
9. Social capital	0.53	0.71	0.25*	0.33*	0.20*	0.24*	0.15*	0.15*	0.24*	0.02*	1
Vif			1.48	1.49	1.43	1.33	1.47	1.44	1.53	1.31	1.49

N = 30,999 *p<0.05

S.D, standard deviation; Vif, Variance Inflation Factor

Table 3. Results of regression analysis of mediated moderation (Dependent variable: Product innovation)

	Criterion: Social capital		Criterion: Product innovation			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Firm Size	0.018 (0.021)	0.023 (0.021)	1.136 (0.133)***	1.080(0.133)***	1.192 (0.135)***	1.142 (0.135)***
Firm SizeSq	0.004 (0.003)	0.004 (0.004)	-0.117(0.016)****	-0.113(0.016)****	-0.126 (0.016)	-0.122(0.017)***
R&D team Size	0.159 (0.009)***	0.163 (0.009)***	0.882 (0.045)***	0.803 (0.046)***	0.887 (0.045)***	0.807(0.046)***
R&D team SizeSq	-0.004 (0.002)	-0.003 (0.001)	0.057 (0.015)***	0.050 (0.015)***	0.068 (0.016)***	0.059(0.015)***
Inn_intensity	0.071 (0.032)**	0.074 (0.032)**	0.686 (0.250)**	0.660 (0.250)**	0.709 (0.260)**	0.680(0.261)**
Inn_intensitySq	-0.003 (0.001)**	-0.003 (0.001)**	-0.023 (0.011)**	-0.022 (0.011)**	-0.023 (0.011)**	-0.022(0.011)*
Main effects						
Education	0.154(0.030)***	0.094 (0.026)***	1.323 (0.137)***	1.415 (0.143)***	0.807 (0.113)***	0.778(0.113)***
Gender	0.149 (0.033)***	0.099 (0.032)***	1.188 (0.149)***	1.125 (0.150)***	0.658 (0.137)***	0.649(0.138)***
Skills	0.061 (0.021)***	0.096 (0.021)***	0.688 (0.092) ***	0.670 (0.092) ***	0.814 (0.099) ***	0.932(0.109)****
Mediated moderation effects						
Gender x Education	-0.212(0.058)****		-1.836 (0.254)***	-1.639 (0.254)***		
Gender x skills		-0.137 (0.062)**			-0.736 (0.265)***	-0.612(0.267)*
Social capital				0.674(0.061)***		0.676(0.066)***
Education x Social capital				-0.392(0.111)***		
Skills x Social capital						-0.409(0.135)**
Log Likelihood	-26818.03	-26824.35	-13511.76	-13395.14	-13539.74	-16651.71

Notes: Standard error in parentheses. *Significance at 5%;**significance at 1%;***significance at 0.1%.
Year and sector dummy variables were included in the analysis but results are omitted here.

Table 4. Results of regression analysis of mediated moderation (Dependent variable: Process innovation)

	Criterion: Social capital		Criterion: Process innovation			
	Model 1	**Model 2**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Firm Size	0.018 (0.021)	0.023 (0.021)	1.227 (0.134)***	1.102(0.128)***	1.167(0.121)***	1.142(0.118)***
Firm SizeSq	0.004 (0.003)	0.004 (0.004)	-0.081(0.016)***	-0.078(0.015)***	-0.087(0.015)***	-0.083(0.014)***
R&D team Size	0.159 (0.009)***	0.163 (0.009)***	0.477(0.043)***	0.365(0.011)***	0.483 (0.043)***	0.371(0.038)***
R&D team SizeSq	-0.004 (0.002)	-0.003 (0.001)	0.005(0.013)	0.009(0.012)	0.011(0.010)	0.015(0.011)
Inn. intensity	0.071 (0.032)**	0.074 (0.032)**	0.533(0.152)***	0.537(0.150)***	0.539(0.152)***	0.541(0.151)***
Inn_intensitySq	-0.003 (0.001)**	-0.003 (0.001)**	-0.025(0.009)**	-0.027(0.009)**	-0.025(0.009)**	-0.027(0.009)**
Main effects						
Education	0.154(0.030)***	0.094 (0.026)***	1.249(0.133)***	1.286(0.138)***	0.852(0.092)***	0.824(0.092)***
Gender	0.149 (0.033)***	0.099 (0.032)***	0.935 (0.147)***	0.816(0.148)***	0.572(0.115)***	0.494(0.117)***
Skills	0.061 (0.021)***	0.096 (0.021)***	0.286(0.089)***	0.257(0.089)**	0.417(0.090)***	0.502(0.098)***
Mediated moderation effects						
Gender x Education	-0.212(0.058)****		-1.413(0.209)***	-1.288(0.211)**		
Gender x skills		-0.137 (0.062)**			-0.712(0.224)***	-0.664(227)**
Social capital				1.142(0.064)***		1.127(0.052)***
Education x Social capital				-0.213(0.113)**		
Skills x Social capital						-0.292(0.111)**
Log Likelihood	-26818.03	-26824.35	-14766.88	-14305.02	-14784.37	-14358.847

Notes: Standard error in parentheses. *Significance at 5%;**significance at 1%;***significance at 0.1%.
Year and sector dummy variables were included in the analysis but results are omitted here.

Table 5. Indirect effect of product and process innovations via social capital at different values of moderators

		Product innovation				Process innovation			
Moderators	Level	Conditional indirect effect	SE	z	P value	Conditional indirect effect	SE	z	P value
Skills diversity									
	Low	0.130	0.043	3.01	0.003	0.058	0.022	2.55	0.011
	High	0.078	0.026	2.99	0.003	0.147	0.049	2.94	0.003
Education diversity									
	Low	0.110	0.026	4.18	0.001	0.072	0.023	3.17	0.002
	High	0.213	0.048	4.42	0.001	0.239	0.055	4.37	0.001

Bootstrap sample size=50

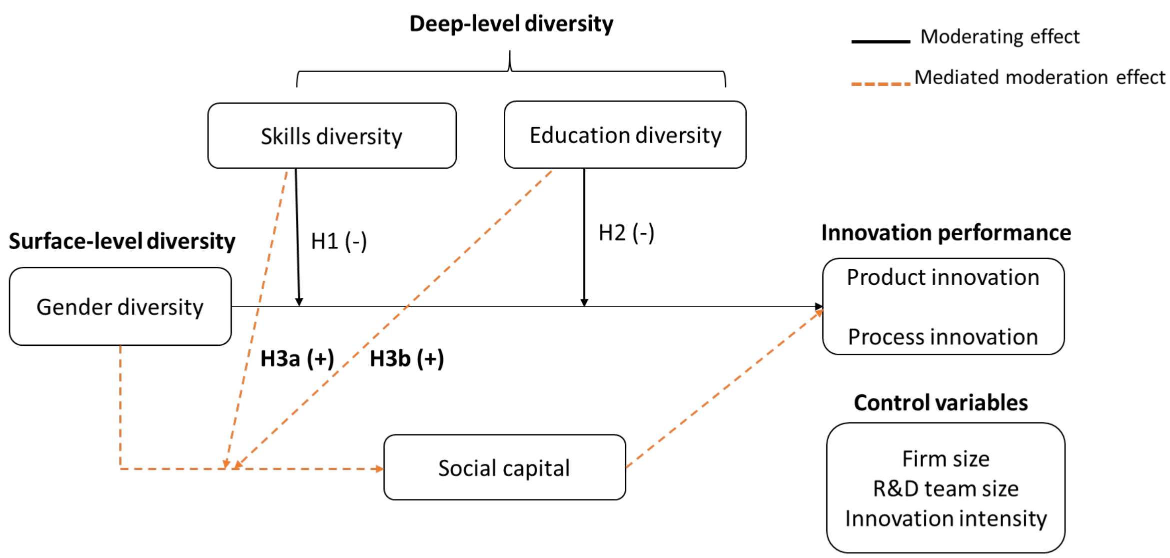

Figure 1. Conceptual model

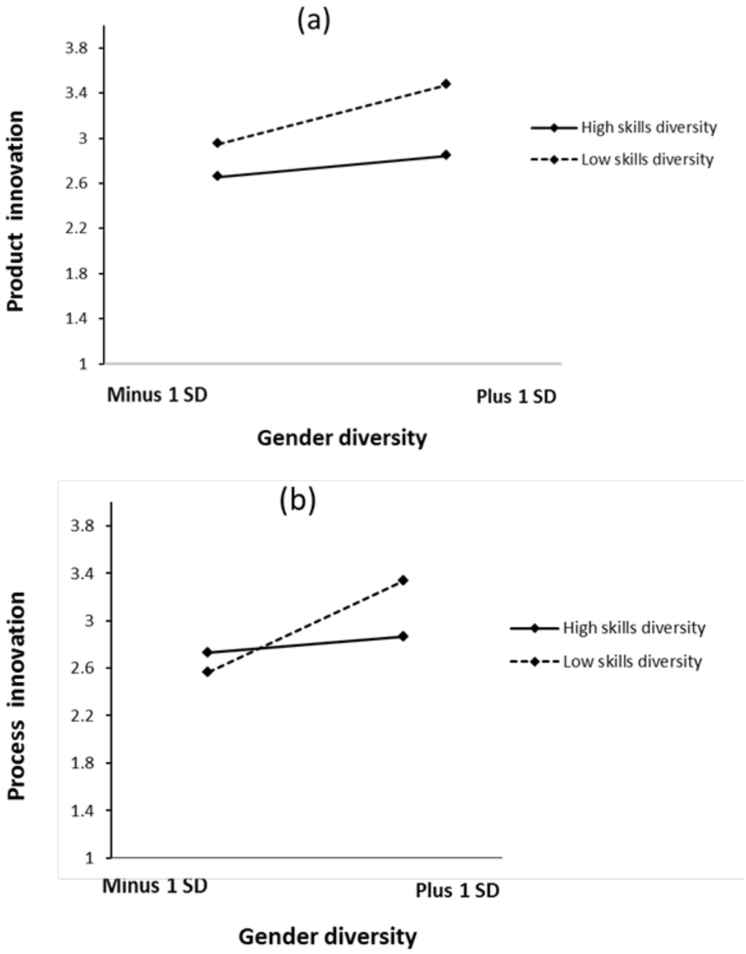

Figure 2. Interaction between skills diversity and gender diversity on product (a) and process (b) innovations

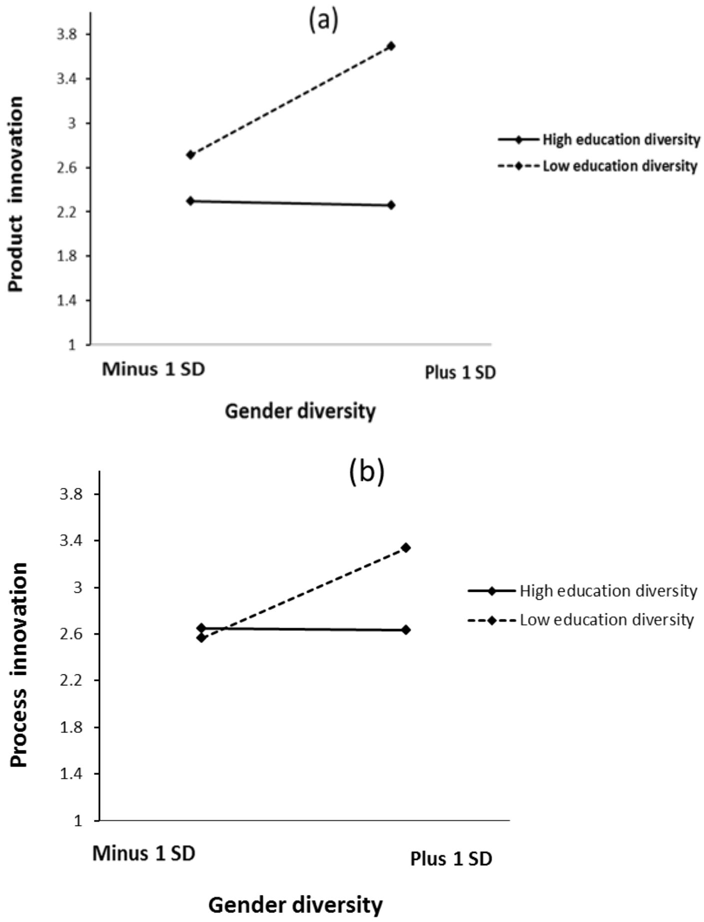

Figure 3. Interaction between education diversity and gender diversity on product (a) and process (b) innovations