Maximizing learning through cohesion: contributions from a nonlinear approach

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Maximizing learning through cohesion: contributions from a nonlinear approach

Abstract

This study explores the relationship between team cohesion and team learning by adopting a nonlinear approach. A quantitative study with a sample composed of 82 organizational teams was conducted. Radial Basis Function (RBF) interpolation models were used and results showed that the best predicting ability was obtained by the Thin Plate RBF model, which revealed that an increase in both dimensions of cohesion leads to an increase in team learning up to a certain threshold. Moreover, our results showed that the maximum value of team learning is obtained at higher values of task cohesion and moderate values of social cohesion.

Keywords:

Team cohesion; Team learning; Nonlinear approach; Radial basis functions

Introduction

In the complex environment that characterizes organizations worldwide, team learning emerges as a central process in the functioning of a group and as a crucial factor for organizations to be effective (Bell et al., 2012; Decuyper et al., 2010). Organizations are sustainable only when they are able to manage uncertainty and to adapt continually to change, rethinking their processes and innovating. As highlighted by Wilson (2001), the main source of an organization's competitive advantage is its ability to learn faster than others. As teams are the cornerstone of modern organizations (Mathieu et al., 2014), team learning appears to be a key driver for team and organizational effectiveness (Decuyper et al., 2010; Koeslag-Kreunen et al., 2018).

Team learning might be conceived either as a group process or as an outcome of group interaction (Argote et al., 2001; Decuyper et al., 2010; Mathieu et al., 2008): the former view regards it as a process through which team members collectively identify, discuss, and solve problems, while the latter is concerned with the result that emerges as a collective property of the team (Bunderson & Sutcliffe, 2003; Rebelo et al., 2018). In the present research, our focus is on team learning as a process through which members acquire, share and combine knowledge in order to achieve the group goals.

Understanding team learning requires an extensive investigation into how team learning can be influenced (improved or inhibited) (Decuyper et al., 2010). Accordingly, previous studies have tried to clarify what drives team learning (e.g., Koeslag-Kreunen et al., 2018; Ortega et al., 2013; Van der Haar et al., 2017).

In this context, Van den Bossche and colleagues (2006) highlight that team learning does not take place "just by putting people together" (p. 514) and emphasize that variables from the interpersonal team context, such as team cohesion, should be considered in order to understand team learning. In line with this, other authors highlight that team cohesion has the potential to stimulate or inhibit processes such as the exchange of ideas, experimentation with new strategies, knowledge sharing, or the occurrence of collaboration and open communication (e.g., Ellis & Bell, 2005; Rodríguez-Sánchez et al., 2017; Wong, 2004) and also suggest, directly or indirectly, the relevance of team cohesion to team learning. However, and although Ellis and Bell (2005) identified an emerging interest in exploring that relationship, few studies have analyzed it (Bell et al., 2012). Therefore, the present study intends to contribute to filling this gap in the literature by focusing on the relationship between team cohesion and team learning.

Cohesion can be defined as the result of all the forces acting on members to remain in the team (Festinger, 1950). Among the different typologies of team cohesion that can be identified in the literature, the two-dimensional conceptualization of this construct, which distinguishes between task cohesion (i.e., the shared commitment among team members to achieving goals that requires collective efforts) and social cohesion (i.e., emotional bonds among team members), is the one that provides the greatest consensus (Chang & Bordia, 2001; Salas et al., 2015; Vanhove & Herian, 2015).

According to Van den Bossche et al. (2006), task cohesion is a supporting condition of team learning. The authors found a positive relationship between task cohesion and team learning and, based on Mullen and Copper's (1994) meta-analysis concerning the relationship between team cohesion and team outcomes, suggested that task cohesion is the critical dimension of cohesion regarding team learning. However, the exploratory study developed by Hardy et al. (2005) emphasizes that high levels of task cohesion can be detrimental to the group by reducing social relations (because the group is strongly focused on the task), producing communication problems and decreasing the team members' contribution to the team (as the distribution of responsibilities becomes much narrower). These findings question the expectation that more task cohesion is always better in terms of learning.

Regarding social cohesion, the literature shows, on one hand, that it may facilitate team learning since, for instance, it increases group communication (Zaccaro, 1991); on the other hand, it may lead to uncritical acceptance of solutions and end up threatening team learning (Van den Bossche et al., 2006). Hardy and colleagues (2005) found that high levels of social cohesion might lead to negative consequences, such as communication problems or a decreased focus on the task, undermining the learning process in the team as a result.

This rationale leads us to ask if there is an optimal level of group cohesion (task and social cohesion) at which team learning might be maximized. In other words, could the relationship between team cohesion and team learning be of a nonlinear nature? Answering this question seems crucial to a better understanding of the relationship between these two constructs.

Although the literature considers that a group is a complex adaptive system where causal relationships are not necessarily linear (Arrow et al., 2000; McGrath et al., 2000), the relationship between team cohesion and team learning has essentially been analyzed in linear models based on the input-process-output framework originally proposed by McGrath (1964). These models might, in some situations, fail to completely capture the shape of the relationships (linear or nonlinear) among the variables involved (Ilgen et al., 2005; Li & Roe, 2012).

In this way, the adoption of approaches that enable the analysis of possible nonlinear relationships between the multiple group constructs should be taken into consideration (Hanges et al., 2004). A natural extension of the linear models to capture possible nonlinear relations existing between predictors and outcomes is the use of nonparametric regression methods, such as kernel regression or regression/smoothing splines in low-dimensional scenarios.

Radial basis function (RBF) regression models are among the most successful nonlinear regression approaches because of their ability to accurately capture the relationships between continuous changes in explanatory variables and outcomes (Rocha, 2008). Due to their good predictive ability, which underlies their capacity to serve as surrogates that successfully mimic the unknown relationships between predictors and outcomes, RBF models have been extensively used in different disciplines (e.g., Buhmann, 2003; Dimas et al., 2016; Rocha et al., 2013). However, in the small group and organizational research, the use of these kinds of designs continues to be the exception, although the need to use more complex designs (such as computational modelling like RBF) has been stressed by different authors in order to model nonlinear relationships such as the ones that might be produced by teams (e.g., Cortina et al., 2017; Hanges et al., 2004).

Accordingly, the present research aims to contribute to the body of knowledge of team learning, by modeling the shape of the relationship between this construct and team cohesion. Specifically, we seek to contribute to clarifying whether the inconsistencies found in previous studies (e.g., Hardy et al., 2005; Van den Bossche et al., 2006; Wong, 2004) are related to the presence of a nonlinear relationship between the constructs under analysis.

The current study aims to advance previous studies in different ways. As team cohesion is one of the most important influencing variables in team learning (Decuyper et al., 2010), clarifying the nature of this relationship will lead to a clearer picture of the conditions that maximize learning in the team context. Moreover, by adopting a nonlinear method that has rarely been used in organizational and group studies, we contribute to highlighting the potentialities of employing analytical approaches that go beyond the widespread linear approach.

Theoretical Framework

Team Learning

Edmondson et al. (2007) identified three leading research traditions in the study of team learning: (a) learning curves (outcome improvement), (b) lab experiments on team members' coordination of task knowledge (task mastery), and (c) field research on the learning process in teams. This third branch, which emphasizes the learning process, encompasses field-based studies that are focused on studying learning in teams. It includes studies that intend to analyze the team learning process itself, and research that is focused on the relationship of several variables with team learning. The present study relies on this third body of research because its sample is made up of real teams in organizational contexts and it is focused on describing the relationship that team cohesion has with team learning.

Despite the lack of consensus that exists around which activities should be included in the team learning process, all of them appear to refer to a process of collective reflection and action (Savelsbergh et al., 2009). In this regard, one of the most accepted and quoted definitions was proposed by Edmondson (1999). In this author's approach, team learning is conceived of as a process of reflection and action, characterized by (a) seeking feedback to evaluate group's performance and to look for improvements; (b) exploring, sharing knowledge and constructively managing differences of opinion; (c) experimenting collectively with new strategies to achieve team objectives; (d) reflecting on past achievements and on future aims; and (e) discussing errors collectively and exploring ways to prevent them.

According to Decuyper et al. (2010), effective team learning is not self-evident. Indeed, it does not just happen by itself, and one can find teams that are very successful and teams that fail in effective team learning (Edmondson, 1999; Van den Bossche, 2006). Therefore, understanding the conditions that foster effective team learning has been a major focus of research (e.g., Decuyper et al., 2010; Koeslag-Kreunen et al., 2018; Zaccaro et al., 2008).

The importance of establishing a supportive environment that fosters a safe exchange of perspectives, where members feel comfortable in sharing knowledge and discussing different ideas, has been found to be critical for promoting team learning (Zaccaro et al., 2008). Indeed, the creation of a joint space characterized by high quality interactions is essential for team learning (Rowe, 2008). In this context, team cohesion, which is one of the critical variables in fostering team interaction, communication and collaboration between members in order to achieve team goals (Ellis & Bell, 2005), has been presented as one of the antecedents of team learning (Brandon & Hollingshead, 2008).

Team cohesion and team learning

Team cohesion was widely studied as a group process (Dionne et al., 2004; Kozlowski & Bell, 2013). However, nowadays, considering the proposal of Marks et al. (2001), who distinguish between group processes and emergent states, team cohesion is conceived of as an emergent affective group psychological state (Kozlowski & Chao, 2012; Mathieu et al., 2008).

Extensively studied with different approaches in multiple contexts (Dion, 2000), team cohesion has mainly been analyzed regarding its relationship both with other group functioning variables and with group results (e.g., Braun et al., 2020; Carron & Brawley, 2000; Chang & Bordia, 2001). These studies, adding to knowledge concerning the association between team cohesion and other team variables, have emphasized the multidimensional character of cohesion (Carless & De Paola, 2000; Dion, 2000). Indeed, as highlighted by Salas et al. (2015), this multidimensional approach is currently dominant in the literature. These authors also emphasize that the most effective cohesion measures are those that assess the social and task dimensions.

In line with previous studies, in the current work, we also adopt the two-dimensional approach. Task cohesion, as already mentioned, concerns the attraction or bonding between group members that is based on a shared commitment to achieving the group's goals and objectives (Van den Bossche et al., 2006). Social cohesion, on the other hand, is related to affective responses of group members to membership in their groups (Sargent & Sue-Chan, 2001) and refers to the attraction within the group that is based on social relationships (Carron & Brawley, 2000; Carron et al., 1985; Rosh et al., 2012).

Adopting the two-dimensional approach, authors such as Mullen and Copper (1994) suggested, in a meta-analysis, that the link between social cohesion and task cohesion with team outcomes can be different and that task cohesion appears to be the critical component. According to these authors, when team members are highly committed to successful task performance, they regulate their behavior toward that end, consequently raising the quality of the results achieved. By contrast, social cohesion appears to be weakly related or even unrelated to team outcomes.

This conclusion, however, should be treated with caution. Indeed, high social cohesion can be detrimental to the team, namely through the occurrence of several group phenomena such as pressures to conform or group polarization (Rovio et al., 2009). However, previous empirical evidence suggests that, albeit in a different way, both facets of team cohesion are potential predictors of desirable team outcomes (Eys & Kim, 2017). For instance, on one hand, task cohesion seems to have a stronger negative effect on perceived social loafing compared to social cohesion (e.g., Hoigaard et al., 2006) and is more strongly related to a reduction in role uncertainty and in absenteeism than social cohesion (e.g., Zaccaro, 1991). On the other hand, social cohesion is more strongly related to member liking than task cohesion (e.g., Zaccaro & Lowe, 1988) and is found to be a predictor of team viability (e.g., Chang & Bordia, 2001).

The findings mentioned lead us to conclude that the relationship between team cohesion (task and social) and team outcomes might be more complex than previously expected. Evidence for this complex relationship was found by Wise (2014), who observed a curvilinear relationship between team cohesion operationalized as network density and team performance in a sample composed of work teams in a service organization.

Regarding the relationship between team cohesion and team learning, despite several studies emphasizing that team cohesion is an important supporting condition for team learning, those studies also suggest the existence of a complex relationship between these variables (Bell et al., 2012). Wong (2004), for instance, found an inverted U-shaped relationship between group cohesion and “local team learning” (i.e., learning within the group), evidencing the nonlinear nature of this relationship. Recently, Marques-Quinteiro et al. (2019) found that an excess of team cohesion impairs team coordination over time. According to the authors, the results found support the idea that teams “perform high when the ties between team members are strong enough to keep them working together, but not too strong to prevent them to openly question and debate their ideas” (p. 13). Since some similarities can be found between the constructs of team learning and team coordination (for instance, both processes involve sharing information about performance achievements and looking for strategies to meet performance standards), these findings can be understood as one more piece of research suggesting the nonlinear nature of the relationship between team cohesion and team learning.

In line with this, we argue that the relationships between both the dimensions of team cohesion and team learning are better explained by a nonlinear function. Concerning the relationship between task cohesion and team learning, we expect a high shared commitment to achieving the group’s goals to emerge as a key driver of team learning (Van den Bossche et al., 2006). Indeed, when team members are highly committed to the group’s goals and tasks, they will be more willing to invest time in reflection activities and in looking for more appropriate performance strategies (Zaccaro et al., 1995). When, on the contrary, task cohesion is low, the team may be less effective in addressing problems together (Maynard et al., 2015), team members may be less motivated to devote time to planning activities, as well as to provide relevant feedback (Zaccaro et al., 1995). In this kind of context, team learning will suffer. Nonetheless, if task cohesion becomes extremely high, criticism might be avoided (Hardy et al., 2005), as well as the identification and test of new paths, and, in consequence, team learning might be at stake. Likewise, as evidenced by Hardy and colleagues (2005) with sport teams, high task cohesion can produce communication inefficiencies and harm effective dialogue, which has been recognized as one of the key fundamental practices to achieving team learning (Senge, 1990; Rebelo et al., 2020). Moreover, when task cohesion gets too high, teams may be overly reliant on their own capabilities, which might prevent them from reflecting on achievements and looking for new ways to address tasks (Marques-Quinteiro et al., 2019; Maynard et al, 2015). Accordingly, the following hypothesis is established:

H1a: There is a nonlinear relationship between task cohesion and team learning.

Regarding social cohesion, evidence from previous studies tend to suggest the nonlinear nature of its relationship with team learning. Van den Bossche et al. (2006) emphasized that social cohesion can have a complex relationship with team learning as, while it might foster learning by increasing willingness to help each other, it might also lead to uncritical acceptance of solutions, undermining learning. When the connectedness between team members is low, the flow of information within the team will be threatened (Zaccaro et al., 1995), preventing team members from engaging in collaborative learning. However, when social integration is too high, members are unwilling to risk social rejection by questioning a majority viewpoint and, as a result, important team learning processes, such as knowledge change and exploring new ideas, may be undermined (Bell et al., 2012). In order to maintain internal harmony, members may agree too quickly without a complete, objective evaluation of the alternatives, which might lead to groupthink (Janis, 1982). Likewise, members of highly cohesive groups may become more concerned about preserving the group's image and their status within the group (Turner, Pratkanis, Probasco, & Leve, 1992) than about looking for new and more appropriate ways to perform their tasks (Pescosolido & Saavedra, 2012).

The nonlinear relationship between social cohesion and team learning can be explained considering social exchange theory and, more specifically, the norm of reciprocity (Blau, 1964). Indeed, group members' affinity for one another may establish a context of more positive and frequent social exchanges among team members (Cohen et al., 2012) that will facilitate team learning. However, when emotional closeness is too high, the obligation felt to reciprocate (Lechner et al., 2010) may lead team members to avoid behaviors like discussing ideas, which are essential for team learning but may be perceived as a threat to the team's harmony. Accordingly, we predict that:

H1b: There is a nonlinear relationship between social cohesion and team learning.

Building on the empirical evidence and arguments presented above, we hypothesize that there is an optimal level of team cohesion (task and social) at which team learning will be maximized. We consider that the relationship between team cohesion and team learning can be viewed through a too-much-of-a-good-thing (TMGT) lens (Pierce & Aguinis, 2013). The TMGT effect is a theoretical principal that accounts for an apparent paradox in organizational life: "ordinarily beneficial antecedents causing harm when taken too far" (p. 314). According to Pierce and Aguinis, after some inflection points, previous positive relationships between antecedents and outcomes cease to increase or become negative. Accordingly, exceeding these inflection points is detrimental because it does not lead to additional benefits or even generates undesirable outcomes.

Concerning social cohesion, we hypothesize that the inflection point will be achieved at a moderate value of this type of cohesion. By enhancing group members' positive working relationships, built through trust and liking among team members (Severt & Estrada, 2015), a moderate level of social cohesion will create the conditions (e.g., open communication, debate of ideas, individual participation in the group) in which team learning will flourish (Marques-Quinteiro et al., 2019; Zaccaro et al., 1995). However, when social cohesion is too high, the pressure to conform might jeopardize team learning (Decuyper et al., 2010), whereas when it is too low the social distance between team members may affect the creation of the conditions necessary for members to learn from each other (Marques-Quinteiro et al., 2019).

Regarding task cohesion, and contrary to social cohesion, we expect that the optimal value of task cohesion at which team learning will be maximized will be higher (and not moderate), as, in line with previous studies, we conceptualize task cohesion as the critical dimension of cohesion (e.g., Mullen & Copper, 1994) concerning team learning. Indeed, members of groups with high levels of task-cohesion will be more willing to invest in helping the team to achieve its goals (Kozlowski & Chao, 2012), as well as to devoting time to looking for effective strategies to problems, testing new approaches and reflecting on achievements. Nonetheless, when task cohesion is extremely high, communication problems might emerge, as well as an excess of confidence and an overall tendency to avoid discussion, which might impair team learning. Thus,

H2: The optimal team learning value is obtained at high values of task cohesion and at moderate values of social cohesion.

Method

Procedure and Participants

Personal and professional contacts were used in order to identify which organizations would participate in the present study. The purpose and requirements of the study were explained to key stakeholders in each organization (CEO or HR managers), along with the benefits of participating in the study (e.g., report on the organization's results). In the organizations that agreed to participate, the selection of teams to be surveyed was based on the application of the following criteria (Cohen & Bailey, 1997): teams (a) must be composed of at least three members; (b) should be perceived by themselves and others as a team; (c) must regularly interact, interdependently, to accomplish a common goal; and (d) have a formal supervisor who is responsible for the actions of the team.

To collect the data from the organizations, we implemented two approaches. Whenever possible, surveys were delivered to the teams and respective leaders by a member of the research team and were filled in during team meetings. This was the procedure followed in the majority of the organizations. Nonetheless, when it was not possible to implement this data collection strategy, surveys were answered online via an electronic platform. In both cases, participation in the study was voluntary and ethical concerns were assured, such as data confidentiality, participants' anonymity, participants' right to withdraw and the use of data solely for scientific purposes. Participants had to sign an informed consent form before answering the questionnaire.

A total of 104 teams and their respective leaders responded to the surveys. Given that the study was conducted at the team level, and to ensure a sufficient number of respondents in each team, teams with a response rate below 50% were dropped from the sample. Additionally, questionnaires where more than 10% of the answers were missing (Bryman & Cramer, 2005) were eliminated. Consequently, 82 teams from 57 Portuguese organizations were retained (the average within-team response rate was 70%). The organizations were mostly from the services sector (73%). Team size ranged from three to 18 members, with an average of approximately six members (*SD* = 3.55). Team members (*N* = 353) were predominantly female (67%) with a mean age of 38 years (*SD* = 12.33); 36.7% had a higher education background and had accumulated an average of six years (*SD* = 5.52) of experience in the team. Regarding the team leaders (*N* = 82), the mean age was 42 years (*SD* =10.86), 57% were male, 55.7% had a higher education background, and had an average of five years of experience as leader of the current team (*SD* = 4.87)

Measures

A multisource approach was implemented in data collection: team members were surveyed about team cohesion, while team leaders were surveyed about team learning and team size. The use of different sources, along with other strategies such as assuring anonymity and confidentiality, contributes to reducing the risk of common method variance (Podsakoff et al., 2003). Leaders were formal and external to the team, they were responsible for the team outputs and were not involved in the team's daily tasks (Morgeson et al., 2010). All variables were measured with previously validated scales that were adapted to the Portuguese language following the procedure proposed by DeVellis (2003).

Team Cohesion

Team Cohesion was measured with the Group Environment Questionnaire (GEQ), originally developed by Carron et al. (1985) for use among sport teams and adapted by Chang and Bordia (2001) to use with work teams. Four items measure task cohesion and other four items measure social cohesion (two are reverse-coded items). The response scale is constituted by five points (1 = strongly disagree; 5 = strongly agree). A sample item for task cohesion is "We have been united in trying to reach the performance goals" and for social cohesion is "Team members rarely socialize together" (reversed item).

Team Learning

Team learning was assessed with Edmondson's (1999) team learning scale (observer survey). This scale is composed of seven items that are rated on a five-point scale (1 = almost never happens; 5 = almost always happens). A sample item is “This team regularly takes time to figure out ways to improve its work performance”.

Control Variable

Since previous studies have shown that team size has an influence on the way the team interacts and achieves its goals (e.g., Curral et al., 2001; Haleblian & Finkelstein, 1993; Mullen & Copper, 1994), team size was included as a control variable. Team size was obtained by asking team leaders about the number of members in their team.

Data analysis procedures

Radial Basis Functions (RBF) are highly useful for the reconstruction of unknown responses from known data (Rocha, 2009) and have been extensively used in different disciplines (e.g., Carr et al., 1997; Buhmann, 2003; Rocha et al., 2013). For any given set of data points, even if poorly distributed and/or small in number, RBF models can provide excellent response surfaces able to explain the nonlinear relationships between independent or explanatory variables and dependent or response variable(s) (Powell 2002). The responses are multivariate in general – in this study we have three predictor variables and thus data points lie in a four-dimensional space where RBF models are calculated.

RBF models are linear combinations of basis functions, $\Phi: \mathbb{R}^n \to \mathbb{R}$, and are radial in the sense that $\Phi(x) = \varphi(||x||), x \epsilon \mathbb{R}^n$, with $\varphi: \mathbb{R} \to \mathbb{R}$ a univariate function and $||.||$ the Euclidean norm. The numerical generation of the RBF model is thus simplified due to the reduction to a univariate function φ. The most commonly used RBFs are the Multiquadric $\varphi(x) = \sqrt{1 + x^2}$, the Thin Plate Spline $\varphi(x) = x^2 \ln(x)$, the Cubic Spline $\varphi(x) = x^3$, and the Gaussian $\varphi(x) = e^{-x^2}$ (Powell, 2002). Because RBF models are interpolation models (i.e., the RBF response coincides with the precise values of the dependent variable for each of the data points), other metrics instead of fitting errors must be used to determine which basis function and what model parameters are most appropriate to model the response. Cross-validation (Stone, 1974) was proposed to find the RBF and the model parameters that lead to an approximate response model with optimal prediction capability and proved to be effective (Efron & Tibshirani, 1993).

There is an increasing evidence that the published results of many papers in psychology fail to hold up when the same experiments and analyses are independently conducted (Open Science Collaboration, 2015). In this context, cross-validation has been proposed as a way to mitigate the ongoing replication crisis of effects in social sciences (Koul et al., 2019; Yarkoni & Westfall, 2017). The idea behind cross-validation to assess the model's predictive ability on unseen data is the same as using a single validation set. By splitting the data set into different subsets, cross-validation repeats the experiment multiple times in a more robust process, giving a more accurate indication of how well the model generalizes to unseen data. The cross-validation error, used in this work for model selection, is a quantification of the model predictive accuracy for out-of-sample data.

For our study, using RBF interpolation models, different sets of parameters and different basis functions lead to different models that have the same response for each of the data points but behave differently (different curvature or shape) between the data points that lie in a four-dimensional space. The RBF model selected is that with the smallest cross-validation error and thus with the best prediction ability (Stone, 1977). The model with the best prediction ability is the response surface which is "closer" to reality (Rocha, 2009). For more details on the implementation of the RBF models used here see Rocha (2009).

Results

Confirmatory factor analysis

We performed a confirmatory factor analysis (CFA), using the maximum likelihood method of estimation to establish the discriminant validity of measurement scales for the three latent variables under study (i.e., task cohesion, social cohesion, and team learning) measured at the group level. The measurement model presented, however, unacceptable fit indices ($\chi2$ (87) = 158.613, $p < .001$, CFI = .85, RMSEA = .10). An analysis of the factorial loadings of the different items on their respective latent variables revealed problems with items 1, 2 and 4 of the team learning scale (i.e., nonsignificant factorial loadings and/or standardized loadings < .40) (Kline, 2016). Accordingly, these items were, sequentially, eliminated from the model. The measurement model with a three-factor structure, without the three items specified above, yielded an acceptable fit for the data ($\chi2$ (51) = 71.595, $p < .05$, CFI = .97, RMSEA = .07). All standardized factorial loadings of the different items on respective latent variables were significant ($p < .001$), and the average was .72, indicating convergent validity. The correlations between factors were moderate (between .33 and .47), indicating discriminant validity (Kline, 2016). In order to have further information about the discriminant validity of the measurement scales, we compared the goodness of fit of the three-factor model with alternative models. Results revealed that the three-factor model outperformed a two-factor model that combined task cohesion and social cohesion ($\chi2$ (53) = 180.211, $p < .001$, CFI = .69, RMSEA = .17) and a one-factor model with all items loading in the same factor ($\chi2$ (54) = 229.181, $p < .001$, CFI = .58, RMSEA = .20).

Data aggregation

Task and social cohesion were examined at the team level but collected at the individual level. Thus, members' responses were aggregated to the team level by computing the average of team members' perceptions on team cohesion. To ensure that the aggregation was appropriate in our sample, we assessed the degree of intra-team consensus by calculating the inter-rater reliability index r_{wg} (James et al., 1993), and the intra-class correlation coefficients ICC(1) and ICC(2) (Bliese, 2000). The average r_{wg} across the 82 teams was .93 for task cohesion and .80 for social cohesion. The ICC(1) for task cohesion was .33 and for social cohesion was .34, whereas ICC(2) for the same variables was .68 and .69, respectively.

Taken together, the r_{wg}, ICC(1) and ICC(2) values provide sufficient justification for aggregating the data at the team level in this study (Bliese, 2000).

Although teams came from different organizations, the organizational level did not account for significant differences in terms of the criterion variable (team learning) and, as a result, was not taken into consideration for further analysis (F (56, 81) = 1.44, *ns*).

Testing of hypotheses

Means, standard deviations, scale reliabilities and the correlation matrix for all variables included in the models are displayed in Table 1. Significant and negative correlation was found between team learning and team size while correlations found between team learning and both task and social cohesion were significant and positive. Task cohesion presented the strongest correlation between independent variables and team learning ($r = .290, p < .01$).

Table 2 presents the cross-validation (CV) errors for the various RBF interpolation models considering different basis functions. The Thin Plate RBF leads to the model with smallest CV error and correspondingly with the best predictive ability which implies that the relationships between the criterion and the predictor variables are better captured by this RBF interpolation model (Rocha, 2009). Thus, the Thin Plate RBF model was selected to assess the relationships between the predictors and team learning. In order to benchmark the relationships obtained by the Thin Plate RBF model, the multiple linear regression model was computed in SPSS (cf. Table 3). As can be seen, team size and team cohesion (task and social) jointly explain 15% of team learning variance (p = .006). As the RBF models are interpolation methods, i.e., they exactly fit each one of the data points, the R^2-value obtained by the Thin Plate RBF model is exactly 1.0 and thus comparison with the R^2-value obtained by the linear model (.15) has little interest.

In order to compare the predictive ability of the Thin Plate RBF and the multiple linear regression model, the CV error for the multiple linear regression was also computed and the result obtained was 1.24, which is worse than the CV error obtained by the Thin Plate RBF model. A 5-by-2 paired *t* test was used to test whether the two models have equal predictive accuracies (null hypothesis) or not. This test was recommended in Dietterich's (1998) highly cited paper as the most appropriate to compare the performance of two models. The result obtained ($t = -4.867$, $p < 0.01$) revealed that RBF model outperforms the linear model. This means that the response is better predicted by the Thin Plate RBF model implying a more reliable response surface that embeds the relationships between dependent and independent variables. Accordingly, this result supports hypotheses 1a and 1b.

The response surface that embeds the relationships between the three predictor variables and team learning lay in a four-dimensional space and thus it is not possible to visualize. However, by fixing the team size it is possible to visually explore the relationships between team learning and both task and social cohesion. Considering a team size equal to the most common team size in our sample (four), the relationships captured by the two models between both cohesion variables and team learning are displayed in Figure 1. The response surfaces obtained by considering the team size equal to the median (five) or the mean (six) are very similar to the response surfaces displayed in Figure 1, considering the team size as equal to the mode.

The plots displayed in Figure 1 are dynamic 3D surfaces, inspection of which from different angles enables a better understanding of the nonlinear trends. For the Thin Plate RBF response surface, an increase in either task cohesion or social cohesion leads to an increase in team learning up to a certain threshold, where team learning ceases to improve. For social cohesion fixed values around 3.5, the nonlinear trend of team learning shows a smooth increase for lower task cohesion values demonstrating a sharper increase for higher task cohesion values up to a certain point, where a plateau is attained. The RBF model points to an optimal task and social cohesion pair of $(4.8, 3.4)$ for maximizing team learning. This finding supports hypothesis 2. The linear response is graphically represented by an increasing linear plane where team learning increases (at a constant rate) for an increase of either task cohesion or social cohesion. This means that the linear model indicates $(5, 5)$ as the optimal cohesion pair.

Discussion

The results from the present study clearly highlight the nonlinear nature of the relationship between team cohesion and team learning. Indeed, our findings reveal that both task and social cohesion contribute positively to team learning up to certain thresholds – beyond these values team learning ceases to improve. Moreover, by showing that the optimal value for task cohesion is higher than for social cohesion, our findings present task cohesion as the critical and primary dimension with regard to team learning (Mullen & Copper, 1994). Therefore, our results are in line with previous studies that suggest that the shared commitment among members to achieve a goal is a determinant in fostering team learning (e.g., Van den Bossche et al., 2006). Moreover, our study extends previous research on the task cohesion – team learning relationship by highlighting that up to a certain (high) point of task cohesion, the increasing pattern of the relationship between these variables changes, and a deflation of team learning tends to occur. Therefore, our study gives support to the preliminary findings identified in the exploratory study of Hardy and colleagues (2005) about the negative consequences of very high levels of task cohesion for team functioning.

Concerning social cohesion, our results reveal that the inconsistency found in previous studies on the influence of this dimension of cohesion on team processes and team results (e.g., Hardy et al., 2005; Mullen & Copper, 1994; Van den Bossche et al., 2006) might be due to the fact that linear models fail to completely capture the trend between these variables.

Indeed, our findings support a positive relationship between social cohesion and team learning up to a medium value of social cohesion; at higher values of social cohesion, this relationship becomes negative. This means that a certain level of liking and closeness among team members, creating a positive environment where members feel free and secure to take risks, is positive for the development of team learning (Zaccaro et al., 2008). Nonetheless, when the emotional bonds are too strong, the threat of groupthink (Janis, 1972) emerges along with the tendency to accept ideas and solutions uncritically (Decuyper et al., 2010). In this kind of environment, team learning tends to be reduced.

Theoretical and methodological implications

One of the main contributions of our research is methodological. To the best of our knowledge, this is one of the first studies in team research that implements RBF models, which have largely been used in other disciplines (e.g., Carr et al., 1997; Golbabai et al., 2012) and proved to be a powerful tool in capturing nonlinear trends between variables. Moreover, by supporting the existence of an optimal level of both dimensions of team cohesion in terms of team learning, our study is one more piece of research that adds to the growing body of evidence on the too-much-of-a-good-thing (TMGT) effect (Pierce & Aguinis, 2013). Additionally, our findings add to the body of knowledge of team learning by evidencing task cohesion as the critical dimension of team cohesion in terms of team learning (Mullen & Copper, 1994). It should be noted, however, that our study also highlights that social cohesion is positive for learning as long as it is maintained at moderate levels.

Practical Implications

The results of our study have significant implications for practice. Indeed, our findings evidence the importance of developing the bond between team members in order to increase team learning within the team. Moreover, our results stress the importance of managing the levels of team cohesion inside the team, by implementing a continual monitoring of team functioning, namely by the leader, to avoid phenomena that can emerge when bonding is too strong, such as groupthink, which is a barrier to learning (Decuyper et al., 2010).

Limitations and Future Research Directions

While it is hoped that our research findings contribute both to the literature and to the practice in several ways, it is worth noting the particular limitations that our research design entails. One of the limitations of the present study is its cross-sectional design, which makes it impossible to draw conclusions about the causality of relationships. Indeed, although the direction of the relationships hypothesized is well supported in the literature, since several studies provide evidence that cohesion is an important supporting condition for team learning (e.g., Bell et al., 2012; Decuyper et al., 2010; Van den Bossche et al., 2006), the reverse direction might also be possible. Indeed, there are some researchers, such as Stagl et al. (2008), who argue that affective states, such as team cohesion or team efficacy, are outcomes of team learning. Future research should overcome this limitation by implementing a longitudinal design.

The adoption of a longitudinal design would also enable the analysis of team dynamics. Indeed, we are aware that teams are complex and adaptive systems (Arrow et al., 2000), so the interactions between their components are not static and constant. The present study, using a cross-sectional design, is not able to answer the call from several authors to study teams taking change and time into consideration (e.g., Roe et al., 2012). As a process, team learning is generated by learning behaviors and members' interactions that change as a function of changing conditions over time. Thus, the understanding of team learning processes needs more research with a temporal perspective (Decuyper et al., 2010).

To extend the findings of the present study and go further in the understanding of the dynamics of the relationship of team cohesion with team learning, it would be interesting, for example, to analyze longitudinal data through growth modeling. This data analysis technique allows an examination of how team learning changes over time, in other words, to ascertain if there is a pattern in the relationship between time and team learning and, also, to examine if team cohesion can help to explain changes in the team learning process over time. Another way to go further in the understanding of the relationship of team cohesion with team learning would be to apply the intragroup longitudinal approach proposed by Li and Roe (2012). Since teams are not homogeneous nor stationary and they do not evolve in the same way (Ramos-Villagrasa et al., 2017), the intrateam longitudinal approach would enable not only analysis of team dynamics over time but also to identify the effect of teams' idiosyncrasies on cohesion and learning dynamics.

Although we adopted a multisource approach in data collection (i.e., team members were surveyed about team cohesion, while team leaders were surveyed about team learning), which may mitigate the risk of common method variance (Podsakoff et al., 2003), all measures used are of a subjective nature. Future studies that intend to study team learning as a process should consider observing and analyzing interaction patterns among team members in the field (e.g., for instance, recording team meetings and using dynamic social interaction analysis techniques), rather than relying only on surveys that evaluate perceptions of previous behavior, because behavioral data tends to be closer to the phenomena of interest (Baumeister et al., 2007; Lehmann-Willenbrock & Allen, 2018).

Some previous research (e.g., Chiocchio & Essiembre, 2009) provided preliminary evidence that the relationship between cohesion and other processes and outcomes may vary across different types of teams (e.g., project vs product teams) and team settings (e.g., organizational vs academic settings). The sample of the present study is from the organizational setting and, although diversified in terms of types of teams, is mainly composed of teams from the service sector (73%). The imbalance between types of teams conditions the possibility of making comparisons between the different types. Thus, in the future, it would be interesting to study the nature of the team cohesion-team learning relationship across different types of teams and team settings.

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Table 1

Descriptive statistics, scale reliabilities and intercorrelations for study variables

	M	*SD*	1.	2.	3.	4.
1. Team learning	3.87	0.72	(.69)			
2. Team size	6.42	3.55	-.22*	-		
3. Task cohesion	4.19	0.47	.29**	-.07	(.83)	
4. Social cohesion	3.38	0.59	.27*	-.10	.37**	(.74)

Note. * $p < .05$; ** $p < .01$. Scale reliabilities are presented in the diagonal.

Table 2

Optimal CV errors for the different basis functions

Multiquadric CV Error	Thin Plate CV Error	Cubic CV Error	Gaussian CV Error
0.88	0.52	1.06	1.56

Table 3

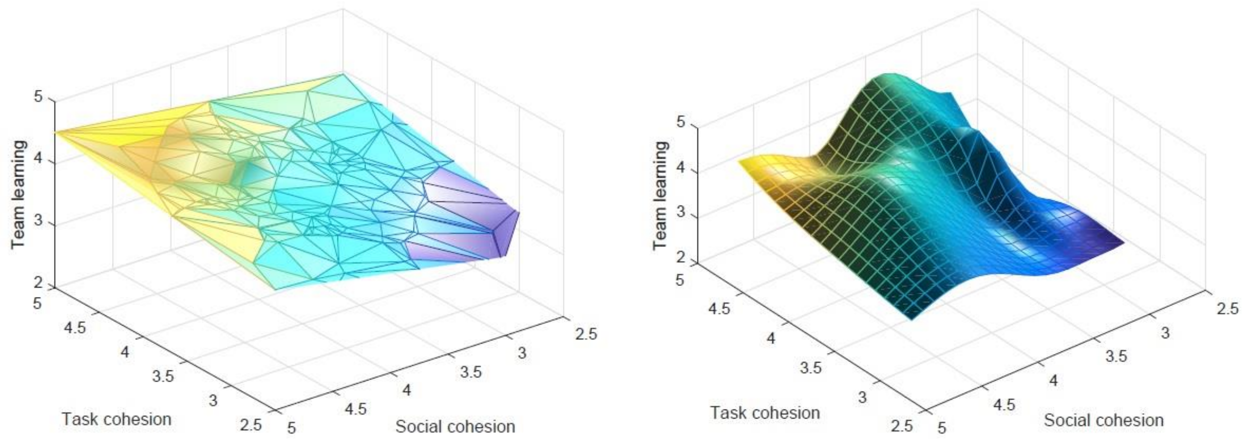
Regression coefficients of team size and team cohesion (task and social) on team learning

Variable	*B*	β	*SE*
Constant	2.06**		.73
Team size	-0.04	-.19	.02
Task cohesion	0.32	.21	.17
Social cohesion	0.21	.17	.14
R^2	.15**		

Note. ** $p < .01$.

Figure 1

Three-dimensional surface of linear and Thin Plate RBF models



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