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AGILE INNOVATION: THE ROLE OF TEAM CLIMATE IN RAPID RESEARCH AND DEVELOPMENT

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Abstract

The impact of team dynamics (as distinct from project management techniques) on speed of R&D project completion was studied in a sample of 35 R&D teams. West's (1990) model of team climate for innovation was measured and analyzed in relation to ratings of project progress over the following nine-month period. Hierarchical linear modeling (HLM) was used to analyse the longitudinal data, and results show that team climate was a significant predictor of project progress. Teams with more positive team climates for innovation progressed significantly faster towards project completion than teams with less positive climates. This result still held after controlling for the initial (pre-survey) estimates of expected project duration, suggesting that project scope (complex, long term vs simpler, short term projects) was not a confound. The results complement previous research that has linked team climate with levels of team innovation. These results support Nonaka's (1990) argument that when multifunctional teams establish positive team processes and interpersonal dynamics, obstacles can be overcome and projects completed much faster.

AGILE INNOVATION: THE ROLE OF TEAM CLIMATE IN RAPID RESEARCH AND DEVELOPMENT

The ability to develop innovative solutions and products can be a major source of competitive advantage for organizations (Foster, 1986; Thamhain, 1996). This is particularly true for research and development (R&D) organizations, whose function is to produce new knowledge, processes and products. R&D organizations have increasingly turned from department-based or matrix structures to team-based structures to achieve greater innovation (Denison, Hart & Kahn, 1996). Teams are thought to be particularly appropriate for projects requiring innovation because they incorporate the views, skills and expertise of a diverse range of members (Watson, Kumar & Michaelson, 1993; Dunphy & Bryant, 1996).

Teams researchers have examined a number of factors that are associated with high levels of team innovation, such as team composition (e.g. Jackson, 1996), leadership (e.g. Keller, 1992), team processes (e.g. Bain, Mann & Pirola-Merlo, 2000) and the organizational context (e.g. Amabile et al, 1996). Such research has focused on levels of innovation (i.e., *how* innovative are a team's outputs?) as the primary dependent variable. However, for innovative organizations, this is only part of the picture. Also critical is the speed of innovation. The value of new products and processes may be severely limited if they arrive too late to beat a competitor to the market.

The importance of speedy new product development (NPD) is highlighted as product cycle times decrease due to increased competition and faster product obsolescence (Filippini, Salmaso & Tessarolo, 2004). Griffin (1997) summarized the previous literature and identified a number of factors that have been associated with faster NPD cycle time. These include contextual factors such as project complexity and technical difficulty; development process factors such as increasing frequency of milestones and overlapping steps; and team structure factors such as the use of cross-functional teams and dedicating team members to fewer concurrent projects. However, there has been very little research examining the impact of team dynamics on speed of R&D project completion.

Tacheuchi and Nonaka (1986) and Nonaka (1990) set out a persuasive argument for using multidisciplinary R&D teams to achieve faster product development. However, they noted that in order to realize this speed advantage, R&D teams need to establish effective team processes. For example, Nonaka (1990) advocates the creation of teams that are cohesive enough for members to feel comfortable sharing all types of information, including redundant information. Such sharing of information can increase the breadth of technical expertise within the team (c.f. Dunphy & Bryant, 1996), and creates opportunities for members to build on each others' ideas and knowledge and hence to develop more innovative outcomes.

A useful framework for understanding team processes related to innovation is West's (1990) model of team climate for innovation. This comprises four factors: (1) vision describes the extent to which team members feel they share clear and valued objectives; (2) participative safety is the perception that the team provides a non-threatening environment where members are able to participate in discussions and influence decisions; (3) task orientation refers to a concern with achieving excellence through high quality work and critical appraisal; and (4) support for innovation is the extent to which the team values and desires innovation, and supports and enables it. Empirical research has supported West's (1990) model: studies from a range of organizational cultures and industries have found positive relations between the above four factors and team innovation (e.g. Agrell & Gustafson, 1995; Burningham & West, 1995; Pirola-Merlo & Mann, 2004; West and Anderson 1996).

Although there have been numerous studies linking speed of R&D to project management and team structure factors, there has been a dearth of research linking team dynamics to speed. This is probably simply due to the difficulty in conducting such research. It generally requires collecting psychometric data from intact team members during the project. This is much more difficult and time-consuming than simply asking a single informant about one or multiple projects (eg “when did they start/finish?”, “did they use a cross-functional team?” etc). Hundreds of team members may have to be surveyed in order to provide enough team-level data for basic statistical analyses. This problem is further exacerbated if there are moderators or confound variables to control for, requiring still larger samples of teams and hence team member responses.

This paper attempts to address this gap by reporting analyses of the relationship between team climate and rates of progress of R&D teams. These analyses are based on data from a study by Pirola-Merlo and Mann (2004), which showed significant relationships between team climate and levels of team innovation. The present article incorporates previously unreported data pertaining to speed of project progress from that study.

Pirola-Merlo and Mann (2004) developed and tested the Aggregation Model of Team Creativity, which links team climate with team creativity and innovation via team member innovativeness. According to Pirola-Merlo and Mann, team climate is relatively stable over time, while the level of team innovation in a project tends to fluctuate from one period to another. Although the impact of climate on innovation may be small from month to month (due to “random” factors such as serendipity, chance breakthroughs or setbacks, difficulties with customers, etc) the pervasive effect of climate adds up, producing large overall effects on team innovation in the context of long-duration projects.

Based on this model, the present study examines the impact of team climate over a several months in a longitudinal study of R&D teams. If we conceptualize R&D projects as being analogous to journeys, involving a number of milestones or steps which must be achieved on the way towards the destination, then this suggests that R&D projects require creativity and innovation at several points. That is, each technical component of a project, or each step of the journey, requires either developing something new (new techniques, solutions, equipment, materials) or else applying an existing idea/solution/technique in a new setting or in a new way. Thus, an R&D project is not just an extended process towards a single innovative product/outcome, but it is also made up of lots of smaller innovations towards that outcome. Thinking about R&D in this way suggests that teams which are *more* innovative will likely complete projects faster, all other things being equal. This is because more innovative teams will be more successful in all of the incremental innovations along the way to project completion.

On the basis of the argument above, and also drawing on the arguments articulated by Tacheuchi and Nonaka (1986) and Nonaka (1990), two hypotheses can be identified relating to team climate and innovation. The first hypothesis is included for the sake of clarity and completeness, although it technically has already been shown to be supported in Pirola-Merlo & Mann (2004) using the same data set.

H1. Team climate for innovation is associated with the level of team innovation achieved by R&D project teams.

H2. Team climate for innovation will be associated with the speed of progress towards project completion over time for R&D project teams.

METHOD

Sample

A sample of fifty-six R&D project teams was studied, comprising 319 team members (47 male, 272 female). These were drawn from four large R&D organizations and were working on a broad range of projects, from relatively small technical service projects, to large ground-breaking applied research with budgets in the tens of millions of (Australian) dollars. At the time of this research, the project teams had formed a median of 21 months previously, and the median length of time until expected project completion was a further 21 months.

Teams with less than three responses to the team climate measure were removed from the analysis. Additionally, some team leaders failed to provide monthly data on team progress, further limiting the sample. Finally, because team-level data were analysed (i.e., individual responses to the team climate measure were averaged within each team), the r_{wg} measure of team-member agreement (James, Demaree & Wolf, 1993) was used to identify two additional teams which had low levels of agreement (r_{wg} values below the recommended criterion of .70) on the team climate measure. After these were removed, the effective sample size for the longitudinal analysis was 35 teams, with a total of 266 individual team members (an average of 7.6 members per team). For these teams, 204 team members responded to the team climate measure (an average of 5.83 members per team), resulting in a response rate of 77%.

Measures

Team members were each sent the Team Climate Inventory (TCI; Anderson & West, 1998) which measures West's four-factor model of team climate for innovation, and were asked to rate their team. The TCI was included as part of a larger questionnaire pack, which included a number of other questionnaires that were part of a broader study of R&D teams (described in detail in Mann (2005).

Eighteen months after the survey, project leaders were interviewed about the project and the events that had taken place since the initial survey. At this time, project leaders were also asked to complete a questionnaire concerning project progress and performance. This included reconstructing and documenting the major events and milestones that had occurred in the months following the team climate survey. The leaders completed a form which profiled the progress that their team had made towards its objectives. In these profiles, the team's month-by-month progress during the period of the study was charted as the percentage-progress towards project completion. Thus, zero-percent progress represented a project just starting from scratch; 100% progress represented the point of project completion (all objectives completed).

In order to provide objectives indicators of innovation, project leaders were also asked to indicate how many (a) new products or processes and (b) patents or patent applications had resulted from the project to date.

Analyses

Correlations were used to test the association between team climate and team innovation (hypothesis 1). Hierarchical linear modelling (HLM) was used to address the relation between climate and progress towards objectives across successive months (hypothesis 2). HLM is an analytical technique that allows researchers to fit regression models at multiple levels of aggregation in a single analysis. In many applied settings individuals are nested within groups. As such, questions such as how group characteristics impact on individuals cannot be tested using traditional regression techniques, which assume independence of observations. HLM analyses allow for nested observations.

The most common use of HLM is to analyse ratings of a group phenomenon (e.g. team or organisational climate) together with individual ratings (e.g. individual/team member motivation or performance). However, HLM can also be used to analyse stability and change in longitudinal data (Bryk & Raudenbush, 1992). In the current study, HLM was used to analyze how far each team had progressed towards project completion. Progress towards objectives (PTO), expressed as a percentage with 100% corresponding to "all project objectives completed", was used as the dependent variable. In this study the HLM analysis first tested whether PTO varied with time –that is, do teams progress across subsequent months? HLM then identifies the extent to which teams vary from one another in their average progress per-month. To the extent that teams do have different rates of progress, the HLM then tests whether this is attributable to some characteristic of the group –in this context, team climate. In other words, HLM was used to answer the question: *does team climate predict the rates of progress towards project completion in R&D teams*?

RESULTS AND DISCUSSION

Relation between climate and level of innovation

The Cronbach alpha values for the TCI scales of participative safety, support for innovation, task orientation and vision were .91, .86, .81 and .89 respectively, indicating good internal consistency. The average r_{wg} values for the climate scales ranged from .94 (task orientation) to .97 (participative safety), indicating a high degree of within-team agreement in the ratings. ICC(1)s (representing proportion of variance attributable to group members) ranged from .14 (task orientation) to .30 (participative safety) –all were significantly larger than zero according to chi-square tests ($p < .001$ for each ICC). These values of ICC(1) are moderate-to-large compared to values typically found in organisational research using multi-level modeling (Bliese, 2000), and support the aggregation of data to the team level.

The correlations between team climate and level of team innovation are shown in Table 1.

Table 1: Correlations between team climate for innovation and objective indicators of innovation (n = 35 teams).

	mean	sd	Correlations 1.	2.	3.	4.	5.
1. Participative safety	3.79	.41					
2. Support for innov.	3.73	.37	.79**				
3. Vision	3.96	.36	.35**	.50**			
4. Task orientation	3.38	.38	.74**	.73**	.43**		
5. New products/processes[a]	2.94	3.56	.17	.34*	.33*	.28†	
6. Patents[a]	1.52	2.27	.16	.26	.13	.18	.33†

** $p < .01$; * $p < .05$; † $p < .10$

[a] Spearman correlations were used for relationships involving the variables indicated due to skewed distributions.

Relation between climate and rate of project progress

Because of the modest sample size (35 teams), statistical analyses were not as powerful as is ideal. Therefore, for the hlm analyses, in order to reduce the type-I error rate, analyses were conducted using a single composite measure of team climate rather than the four separate scales. This was supported by the large inter-scale correlations (ranging from .50 to .77). The reliability of the composite team climate measure was .95.

The HLM analysis was conducted in a number of steps. Firstly, the one-way ANOVA model was tested. This is a regression model in which team *j*'s progress towards objectives (PTO) at time *i* is predicted according to the Model 1 equations shown in Table 2. In this model, an intercept term but no slope term is included (ie, no effects of time are modeled). Here, β_{0j} is the average value of PTO for team j, γ_{00} is the grand mean (i.e. mean for the entire sample) of PTO, and U_{0j} is the deviation of team j's average PTO from the grand mean PTO. Finally, r_{ij} is a level-1 residual term, which in this context indicates the within-team (across time) variation in PTO. In other words, PTO in any given month for team *j* is the grand mean of PTO for all teams in the sample, plus or minus team *j*'s average deviation from the grand mean.

Table 2: Formulas for three HLM models

Model 1:

L1 (within groups; change over time): PTO = $\beta_{0j} + r_{ij}$

L2 (between groups): $\beta_{0j} = \gamma_{00} + U_{0j}$

Model 2:

L1: PTO = $\beta_{0j} + \beta_{1j}$ (time) + r_{ij}

L2: $\beta_{0j} = \gamma_{00} + U_{0j}$

L2: $\beta_{1j} = \gamma_{10} + U_{1j}$

Model 3:

L1: PTO = $\beta_{0j} + \beta_{1j}$ (time) + r_{ij}

L2: $\beta_{0j} = \gamma_{00} + U_{0j}$

L2: $\beta_{1j} = \gamma_{10} + \gamma_{11}$ (team climate) + U_{1j}

The one-way ANOVA model resulted in variance estimates for U_{0j} and r_{ij} of 343.48 and 253.61 respectively. The value of U_{0j} was significant (chi-square (34) = 314.39**), and the ratio of U_{0j} to r_{ij} shows that 58% of the variation in progress was between teams.

The second model incorporated time as a level-1 predictor. Time was measured in months, from 0 (time of the initial questionnaire) to 8 (nine-months later). This model tested whether time accounted for any of the systematic within-team variation in progress. Model 2 is shown in Table 2. It depicts a particular team's progress at any given month as a function of the grand mean PTO, a team-level residual from the grand mean, as well as an overall-sample effect of time, and an associated team-level residual from that effect. The results show that both fixed effects (γ_{00} and γ_{10}, i.e. the average intercept and slope terms respectively) were significant (t(34) = 6.68** and t(34) = 6.09** respectively). Respectively, these indicate that teams were significantly greater than 0% towards objectives at time=0, and that time had a significant effect on PTO (ie, teams progressed over time). Further, the random effect was also significant. That is, there was significant between-teams variance in the impact of time (variance(U_{1j}) = 14.28, chi-square (33) = 330.96**). The value of the fixed coefficient of time was 4.27, and the standard deviation of the random coefficient of time was 3.78. Thus, teams on average progressed 4.27% towards objectives per month. A team one standard deviation above the mean progressed 8.05% per month.

Finally, having accounted for the effects of time, team climate was entered as an additional predictor in a third model. Team climate was used as a level-2 predictor, as it was conceptualized as influencing progress across all of the time periods. This third model is shown in Table 2.

This model shows that at any particular point in time, a team's progress is a function of their initial progress (the intercept term), plus the effect of time on that team. Having shown in Model 2 that teams vary in their rates of progress (ie there was significant between-teams variation in the slope, or effect of time on PTO), the third model tests whether this variation is accounted for by team climate. In other words, this tests whether teams with a positive climate have a greater positive effect of time (ie, progress faster) than teams with negative team climates. Team climate was grand-centred, meaning each team's deviation from the grand mean of team climate was used as the predictor, rather than the raw value. This makes the coefficients more easily interpretable. The results are shown in Table 3.

The results show that teams with climates close to the sample average of 3.63 tended to progress towards their objectives at a rate of approximately 4% per month. However, of particular interest was the significant effect of team climate. For each one point above 3.63 on the team climate scale (a 1-5 scale), a team could expect an additional 4.44% progress per month. Thus, team climate was able to account for significant variance in the R&D teams' progress towards objectives.

Table 3: Fixed and random effects for Model 3

Fixed Effects	**Coefficient**	**Standard error**	**t (df)**	**p**
Mean initial progress, γ_{00}	27.26	4.05	6.73 (34)	< .001
Mean monthly gain, γ_{10}	4.34	.66	6.59 (33)	< .001
Mean effect of team climate, γ_{11}	4.44	2.07	2.15 (33)	< .05
Random Effects	**Variance component**	**chi-square**	**df**	**p**
Initial performance, U_{0j}	527.84	579.50	33	< .001
Time (monthly gain), U_{1j}	11.96	273.54	32	< .001
Level-1 error, r_{ij}	61.78			

Post-hoc analyses

One potential problem with the hlm analysis is that the results are ambiguous in terms of the direction of causality. It is possible that working on a large, long-term project may cause a team to have lower team climate than working on a shorter project. In other words, the direction of causation may be the opposite of what has been argued above: project duration may affect team climate rather than the other way around. This possibility was examined in a post-hoc analysis.

In order to examine this question of directionality, team climate was correlated with project leaders' estimates of the months remaining until project completion. Project leaders were asked to estimate the time until project completion on two occasions: once immediately prior to the first questionnaire (time = 0), and again approximately 18 months later, at the same time that they were asked to profile the team's progress towards objectives. If project duration affects team climate, then significant negative correlations are expected with team climate. However, if team climate affects rates of progress, then the initial estimate of project duration will show no correlation with team climate, although the second estimate may shown an association (because by this time, climate has already impacted on progress to date). Spearman correlations were used because expected project duration was not normally distributed. The correlations are shown in Table 4.

Unfortunately, only 11 project leaders responded to the initial questions (these preceded the administration of the TCI by 1-4 weeks), and only 23 leaders answered this question in the post-project interview/questionnaire administration. As a result of the low sample sizes, these results are only indicative. In fact, a power analysis indicates that even using the second estimate of project duration, with a sample size of 23, there would only be sufficient power to detect very large effects (with power = .90, the population correlation would have to be above .62 for detection).

Table 4: Spearman correlations between team climate and estimated time to project completion.

	Estimated # of Months to Project Completion	
	First estimate (n = 11)	Second estimate (18 months later) (n = 23)
1. Participative safety	.17	-.11
2. Support for innovation	-.18	-.21
3. Vision	.14	-.36†
4. Task orientation	.06	-.12
5. Team climate (total score)	-.03	-.23

† $p < .10$

CONCLUSION

The results show that hypothesis one was supported, with significant correlations between team climate and at least one of the objective indicators of innovation: number of new products/processes.

The hlm analyses supported hypothesis two, indicating that team climate had a significant effect on the progress that teams experienced from one month to the next.

Post-hoc analyses were consistent with the argument that team climate influences speed of progress rather than the other way around. These correlations were close to zero, particularly for the initial estimates. Given the low sample size and power for the post-hoc analysis, it is certainly not conclusive. It does, however, show that there is at the least no empirical evidence from the available data which casts doubt the assertion that it is climate which influences speed of progress towards objectives.

These results are an important contribution, because they contribute to the existing literature showing links between team climate and innovation. These results further show that not only do teams characterized by support for innovation, participative safety, task orientation and vision tend to produce more innovative outputs, but they tend to do so at a faster rate than other teams. That is, this study supports the application of West's (1990) model of team climate to predict *rates of progress* on innovative projects as well as *levels of creativity* of project outcomes.

Additionally, the results of this study support Pirola-Merlo and Mann's (2004) Aggregation Model of Team Creativity, which asserts that the work environment has a pervasive effect on innovation over time. Indeed, the data reported included progress over a period of nine months following the measurement of team climate. Over this period, team climate was seen to make a significant difference to the rate of progress towards objectives. Thus, Pirola-Merlo and Mann's argument that the effects of the work environment "add up" over time applies not only to how innovative outcomes are, but also to the speed of their development.

For practitioners, this study supports attempts by R&D organizations to speed up product development through adoption of team-based structures. However, consistent with Nonaka's (1990) argument, structure alone will not suffice. Rather, organizations must attend to the work environment including team climate and team processes if project teams are to become hotbeds for fast development of innovative new products.

The impact of team climate in the hlm analysis (Model 3) may appear modest: a 1-point improvement above the sample average for team climate translates into an expected increase in monthly progress of 4.44%. However, as well as being statistically significant, this result is certainly also of great practical importance. Relative to the 4.34% progress per-month exhibited by teams with average team climate, the team 1-point higher shows double that progress (ie, 4.34 + 4.44 = 8.78% per month).

In the current sample, this corresponds to an expected total project duration of approximately 12 months for the team that is 1-point above average in climate, compared to the expected 24 months. The implications are then multiplied when one considers the cost implications of multiple team members. For example, if the project is finished one year early, a 10-person project team can be allocated elsewhere, potentially saving the organisation 10 times the cost of a person's salary and on-costs. According to the costing model of the author's institution, the salary and on-costs of a middle-level academic is approximately US$80,000. Thus, the annual salary of a team of twelve researchers would be close to a million dollars. This estimate is undoubtedly conservative compared to industrial R&D organisations' costing models.

These approximate estimates of the cost implications, as large as they are, pale into insignificance when the effects are thought of in terms of time to market for new products. The success of an organisation's new products depends to a large extent on whether the market is growing, stable or declining (Bean & Radford, 2000). Halving the time required to get new technologies and products to the marketplace could literally make or break the success of a new innovation and have major financial implications for the firm.

The current study examined 35 R&D teams working on a variety of types of projects. One of the major difficulties of conducting this type of study is obtaining large numbers of intact teams to provide data. This is particularly challenging where longitudinal data or repeated measures are involved, and attempting to capture objective measures of performance increase the difficulty still further. Ideally, this study would be based on a larger sample, enabling a greater degree of statistical power and confidence in the generalisability of the results. A larger sample would also enable more fine-grained analyses. For example, research teams and development teams could be compared, to see if there are systematic differences between different types of projects. Additionally, a larger sample would enable a wider range of variables to be incorporated in the analyses, such as team leadership and organisational factors.

Another limitation of this study was the reliance on project leaders' memories of events to reconstruct their projects' progress over months. This aspect of the design helped minimise major gaps in the data that would have occurred if monthly questionnaires had been administered. However, it does raise some concern about the reliability of the PTO measure. This concern is minimized, though, when one considers that the average slope of progress for a team essentially requires an accurate recollection of the beginning point and end point. The failure to recollect fluctuations in the intervening months would have an impact on the variance estimates (specifically the estimate of how much variation in PTO was within-teams (across time) compared to between-teams). However, the main finding, that the average slope for a given team is influenced by the team's climate, would not be greatly affected. Additionally, when leaders estimated the time until project completion prior to the survey administration, and once again 18 months later, the two estimates showed a large correlation of .79 ($p < .01$). The agreement between these estimates provides support for the reliability of the leader's judgements about project progress.

The present study is consistent with previous theories of team innovation (e.g. Pirola-Merlo & Mann, 2004; West, 1990), adding to the growing body of literature linking team climate to innovation. The findings of this study are also consistent with propositions by other researchers that multidisciplinary R&D teams can shorten product development time, so long as effective team processes are developed (c.f. Ancona & Caldwell, 1992; Nonaka, 1990; Tacheuchi & Nonaka, 1986). This makes perfect theoretical sense, as team processes are strongly linked with levels of team innovation, and teams that can be more innovative should reach breakthroughs that enable them to progress faster. In other words, teams that are *more* innovative, should generally also innovate *faster*, at least in long-term, complex projects such those typical in R&D settings. By providing empirical evidence to support this assertion, this study makes a novel contribution to the team innovation literature.

As noted above, there are a number of difficulties in conducting research into workplace teams, particularly longitudinal research. However, given the estimated benefits outlined above, the importance of this research cannot be understated. Hopefully the potential financial benefits for organisations that arise from understanding how to facilitate innovative, rapid product development teams will result in closer linkages between organisations and teams researchers, to further this important line of investigative research.

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