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Performance of student software development teams: the influence of personality and identifying as team members

Conal Monaghan[a]*, Boris Bizumic[a], Katherine J. Reynolds[a], Michael Smithson[a], Lynette Johns-Boast[b] and Dirk van Rooy[a]

[a]*Department of Psychology, Australian National University, Building 39, Canberra 0200, Australia;* [b]*College of Engineering and Computer Science, Australian National University, CSIT, Canberra 0200, Australia*

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One prominent approach in the exploration of the variations in project team performance has been to study two components of the aggregate personalities of the team members: conscientiousness and agreeableness. A second line of research, known as self-categorisation theory, argues that identifying as team members and the team's performance norms should substantially influence the team's performance. This paper explores the influence of both these perspectives in university software engineering project teams. Eighty students worked to complete a piece of software in small project teams during 2007 or 2008. To reduce limitations in statistical analysis, Monte Carlo simulation techniques were employed to extrapolate from the results of the original sample to a larger simulated sample (2043 cases, within 319 teams). The results emphasise the importance of taking into account personality (particularly conscientiousness), and both team identification and the team's norm of performance, in order to cultivate higher levels of performance in student software engineering project teams.

Keywords: performance; teams; personality; team identification; team norms; software development; software engineering

1. Introduction

Real-world skills and competencies need to be developed in students to replicate the software engineering workplace (Denayer et al. 2003; Mills and Treagust 2003; Schachterle and Vinther 1996). Small project teams are regularly employed in software engineering to achieve myriad goals. Recently, educators and researchers have argued that student learning should be enhanced by moving away from the standard curriculum and focus on student project teams (Denayer et al. 2003; Johns-Boast and Flint 2009, 2013; Lima et al. 2007; Mills and Treagust 2003; Powell 2004). Even though it is commonly assumed that teams by their nature will perform more effectively than individuals (Cartwright and Zander 1953), the reality is far more complex. Accordingly, there is a need to focus more on the characteristics and practices that facilitate higher levels of performance in student project teams.

The personality perspective is a dominant area of performance research, with foundations in the original attempts to determine academic achievement through variations in cognitive functioning (Binet 1903; Webb 1915). Differences in individuals' personalities have been found to predict the

*Corresponding author. Email: conal.monaghan@gmail.com

performance of individuals (Poropat 2009, 2011), as well as the performance of teams as a whole (Halfhill et al. 2005). The personality of team members has strong empirical backing as a crucial factor in understanding the performance of engineering project teams.

Research in self-categorisation theory, with its roots in Gestalt theory, has demonstrated that psychological group membership is more than the mere knowledge that one belongs to a group (Turner et al. 1994). Through identification as a member of a group or project team, regardless of their personal dispositions, individuals can internalise the values and performance norms of the project team (Hogg and Abrams 1988). Considering the team environment primarily as the interactions of interdependent individuals may underplay this capacity of the team environment to influence thoughts, feelings and behaviours of its membership. To increase the level of performance of student software engineering project teams, it is important to investigate both personality and group perspectives in order to understand their influences and practical consequences.

1.1. *Personality's influence on performance*

At the heart of the personality based approach is the concept of a set of stable and enduring patterns of thoughts, feelings and behaviours that define who we are as individuals. One of the central conceptualisations of personality is the trait approach, which describes personality as the product of enduring internal characteristics (Digman 1996). The five-factor model of personality provides a highly valid, reliable, concise and widely accepted framework for describing personality traits. This model suggests that there are five most fundamental traits on which people differ: conscientiousness, agreeableness, openness to experience, extraversion, and neuroticism. Evidence suggests that these traits have a biological foundation and can significantly predict how individuals will generally act and perform across their lifespan and in different physical and social environments (Costa and McCrae 1988, 1992; McCrae and Costa 1996).

From the perspective of the five-factor model of personality, team member performance is determined by the expression of specific personality traits interacting with the team environment. Although earlier inconsistent and non-concise approaches concluded that there was no correlation between specific personality traits and performance (Guion and Gottier 1965), with the establishment of the five-factor model, a large body of evidence has linked all five traits to performance across various fields (Barrick, Mount, and Judge 2001). Two of these traits, conscientiousness and agreeableness, are of particular concern to the realm of student project team performance.

Conscientiousness is the trait most widely and consistently linked to performance, and describes the degree to which one is responsible, organised and studious (Digman 1996). Research has shown that conscientious individuals outperform non-conscientious individuals in overall performance in the workplace (Barrick and Mount 1991; Barrick, Mount, and Judge 2001), in primary and secondary schooling (Poropat 2009), and during post-secondary education (Furnham and Chamorro-Premuzic 2004; O'Connor and Paunonen 2007). Furthermore, conscientiousness has been more strongly correlated with academic performance than measures of cognitive ability, such as intelligence (Poropat 2011).

Conscientiousness is a personality trait central to team functioning. Higher levels of conscientiousness have been linked to team-oriented performance (e.g. Barrick, Mount, and Judge 2001; Le et al. 2011), supervisory ratings of team interactions and performance (Mount, Barrick, and Stewart 1998), a tendency to engage in higher levels of organisational citizenship behaviours (e.g. assisting other employees who have been absent from work and supporting co-workers who have personal problems), and lower levels of non-productive group behaviours, such as social loafing and free riding (Albanese and Van Fleet 1985). Conscientious team members also contribute more in group situations than non-conscientious team members (LePine and Van Dyne 2001).

Agreeableness is the second influential personality trait within the team environment. Agreeableness encapsulates those aspects relating to one's social and interpersonal characteristics, such as being cooperative, altruistic and trustful (Digman 1996). Individuals who are highly agreeable are more likely to work cooperatively (LePine and Van Dyne 2001), display higher levels of teamwork (Barrick, Mount, and Judge 2001; Mount, Barrick, and Stewart 1998) and be more motivated to help others in need (Graziano et al. 2007) than individuals low on agreeableness. Research also suggests that team members high in agreeableness feel positive emotions while being cooperative, and negative emotions while engaging in quarrelsome behaviours (Cote and Moskowitz 1998).

Agreeable personalities facilitate higher levels of team performance only if positive interpersonal interactions are essential to performance. Agreeableness does not represent performance specific characteristics, but captures interpersonal characteristics, such as being cooperative and considerate (Digman 1996). As a result, agreeableness will predict performance only when interpersonal characteristics, such as being cooperative, influence the ability of a team to perform effectively. Although positive teamwork behaviours are often assumed to facilitate higher levels of team performance, the importance of teamwork is dependent upon the specific demands of the team's environment (Barrick et al. 1998).

Behaviour of a group can also be explored through the personalities of the respective team members. If the team consists of team members high on a particular personality trait (e.g. conscientiousness), then the mean (or average) team personality can be seen as being high on that trait (e.g. the whole team might be more conscientious) (Halfhill et al. 2005). Average team personality is the most common conceptualisation of the team's personality, as reflected in the largest and strongest body of research (Barrick et al. 1998; Halfhill et al. 2005; Peeters et al. 2006). Mimicking the individual level of analysis, mean levels of conscientiousness and agreeableness have been linked to higher levels of teamwork and team performance (Barrick et al. 1998; Neuman, Wagner, and Christiansen 1999). Although a strong body of evidence supports the possibility of predicting the performance of student software engineering project teams from the personality perspective, the conceptualisation of a stable and enduring personality regardless of the social environment has been questioned (Mischel 1973).

1.2. *The influence of identifying as a team member*

In sharp contrast with the personality-based approach which argues that personality is stable and enduring, a large body of research demonstrates the ability of the group or team to have a real psychological impact on its members (e.g. Tajfel et al. 1971; Van Knippenberg and Ellemers 2003). Self-categorisation theory argues that it is necessary to understand the entire social dynamic, and not simply the personalities of the constituent team members, in order to explain group behaviour (Turner et al. 1987). According to this theory, the individual's identity is not fixed and enduring, but is transient and the product of a comparative process in the context of the current social situation (Turner et al. 1994). A group is more than, and fundamentally distinct from, the personalities of its members (Hogg and Abrams 1988).

Under the self-categorisation framework, individuals can define themselves in two ways (Brown and Turner 1981). First, they can draw attention to those characteristics of the self, such as personality, that are distinct and unique ('I' or 'me') when compared with others. Second, they can define themselves in terms of the similarities that exist within a social category (e.g. Australian, student, project team member), which are distinct from the members of a different social category (Hogg and Abrams 1988). When defining themselves in terms of their social identity ('us' or 'we'), interactions between individuals are in the context of their respective groups (Turner et al. 1994).

When individuals identify strongly as group members, they become depersonalised, acting as interchangeable and self-stereotyped group members (Turner et al. 1994). It is this process of social identification that allows the group to have a real psychological influence on the behaviours, cognitions and emotions of the other group members, changing orientation of the team members to the world to that of the group (Bizumic et al. 2009). As identification with the group increases, the more the individuals within the group are motivated to increase the standing of their group – even if this is at a cost to themselves personally (Van Knippenberg 2000).

Research suggests that group identification increases team-orientated performance and motivation to work on the behalf of the team (Van Knippenberg 2000). In organisational research, team identification has been linked to increased team loyalty and to team contributions beyond the individuals' assigned tasks (Haslam 2004), and to lower levels of social loafing (Harkins and Szymanski 1989). This research suggests that identification as a member of a team is an important factor in the degree to which the team member will perform on the behalf of the group.

Group norms express important aspects of the group's identity, which are internalised through team identification. It is these team norms that challenge and modify the individuals' personal views, cognition and behaviours (Bizumic et al. 2009). Many studies have shown the ability for the group norm to influence the individual group member's behaviour in areas of individualism and collectivism (Jetten et al. 2006), de-individualisation (Postmes, Spears, and Lea 1998) and bullying (Ojala and Nesdale 2004). In the educational domain, the perceived learning norms of an academic discipline can influence whether respective students adopt a surface or deeper level approach to their learning (Smyth et al. 2013). In the same vein, group norms of performance can act to increase or decrease performance in a team (Van Knippenberg and Ellemers 2003). While identifying as a member of a project team, internalisation of the perceived normative performance levels allows the team environment to significantly influence the performance of the team's members (Paulus and Dzindoley 1993; Schmader 2002; Shih, Pittinsky and Ambady 1999; Spencer, Steele, and Quinn 1999).

Identification with the project team may play a central role in the relationship between team norms and performance. A study by Bizumic et al. (2009) found that identification with one's school partially accounts for, or mediates, the relationship between the school climate factors (e.g. perceived fairness and shared goals between staff and students) and individual psychological properties such as anxiety and depression. Both school climate and team norms represent characteristics of the social environment that can be used to form part of the social identity. Team identification may similarly partially account for or mediate the relationship between team norms and performance.

1.3. *The current study*

To date, it seems that no published studies have explored the influence of both personality and social identity processes in understanding performance. With foundations in psychological research, the current study aims to investigate the influence of these two perspectives on the performance of software engineering software teams. The results have practical and important applications in cultivating performance in these student teams.

Based on the literature reviewed, we first hypothesised that team averages of the personality measures of conscientiousness and agreeableness would be positive predictors of team performance. Second, we hypothesised that team averages of team identification and a perceived team norm of performance would positively influence performance. Third, we hypothesised that, based on the findings of Bizumic et al. (2009), team averages of team identification would mediate the relationship between the team norm of performance and the performance of the project teams.

2. Method

2.1. *Participants*

One hundred and six Australian National University third- and fourth-year software engineering students participated in the study as part of a whole academic year (two-semester) course in either 2007 or 2008. Of the 106 participants, 80 participants completed at least three out of four phases and were included in the current study. These 80 participants consisted of 74 males and 6 females whose ages ranged from 19 to 39 years with an average age of 22.11. There were 16 projects and each participant was assigned to one of the 16 project teams for the entire duration of the project.

2.2. *Variables*

The degree to which the items in a measure assess the same construct is known as internal consistency. Cronbach's alpha (α) estimates internal consistency by measuring the similarity in participants' responses on each of a scale's items. Values higher than .70 are usually considered satisfactory (see DeVellis 2012). As will be described later, all scales had satisfactory internal consistency.

2.2.1. *Personality traits*

Student's personality traits were measured with shortened versions of the International Item Personality Pool's measures of conscientiousness and agreeableness (IPIP-NEO) (Goldberg 1999), which act as public-domain proxies for the well-established NEO PI-R (McCrae and Costa 1996). Each of the two scales used to measure conscientiousness and agreeableness consisted of 24 items. An example item from the Agreeableness Scale ($\alpha = .74$) is 'I love to help others' and from the Conscientiousness Scale ($\alpha = .84$) is 'I am always prepared'. Each item was rated using a five-point Likert scale from *disagree strongly* (*1*) to *agree strongly* (*5*).

2.2.2. *Group norm and identification*

The degree to which students identified as group members was measured with a social identification measure ($\alpha = .86$), which included four items representative of widely used items from social identity research (Haslam 2004). The students' perception of their group norm of performance was measured with a 7-item scale designed to measure both perceptions of the norm of overall team performance and the degree to which the team worked cooperatively ($\alpha = .93$). An example item used to measure team identification is 'I am pleased to be a member of this group', and to measure the group norm of performance is 'In this group it feels like we are very effective in achieving group goals'. The items of both scales were rated using seven-point Likert scales, ranging from *disagree strongly* (*1*) to *agree strongly* (*7*).

2.2.3. *Team performance*

Team performance was measured at four points through the year, according to the course assessment scheme. Each semester is broken into two terms and at the end of each term, teams' performance was assessed to ascertain the team's ability to deliver quality project artefacts at each milestone. Project milestones included scope and requirements definition, prototyping, architecture and design, implementation and testing of the solution and development of associated technical and user documentation. Teams were also assessed on the quality of their overall project governance and management process by the course supervisor. The final assessment examined the delivered software and all artefacts. Each team received a team mark based on the assessments over both semesters. Individual performance was determined by moderating the team mark with a peer assessed rating of team members' contribution. Thus each member of the team received an individual mark, based on the output of the team as a whole, but representative of their individual contribution to the teams' output. Peer assessment was used to determine the individual's contribution to the overall team output and to foster team-orientated performance. Using peer assessment in this way overcomes many of the problems associated with teamwork where all members of the team receive the same mark, such as social loafing and free riding (Clark 2005; Kennedy 2005; Oakley et al. 2004). Teamwork accounted for 65% of students' total grade. Individual learning was measured through reflective writing and examination. Individual performance was not included as part of the performance measure used with this study.

2.3. *Procedure*

The same procedure was adopted in both 2007 and 2008. At the beginning of the year, based on expressed preference, academics assigned students to a project group. Groups then met with their clients to discuss the details of the problem for which they were to develop a software solution. Teams continued to meet with their clients regularly throughout the project (for more details on the course itself, see Johns-Boast and Flint 2009, 2013). The recent literature has highlighted the importance and efficacy of basing the curriculum on team-based projects with continual and multi-phase assessments (Denayer et al. 2003; Lima et al. 2007; Powell 2004).

A survey was given to the participants in four phases, during their classes. The first phase was conducted in March, the second in June, the third in August and the fourth in September. In the first phase, students filled out the personality trait measure and basic demographic information. During the second, third and fourth phases the students completed the group identification and group norm of performance measures. Groups met for a minimum of three hours per week of face-to-face interaction, and frequently up to 8 or 10 hours per week. Participation was a compulsory component of successful course completion and was measured through peer assessment. In order to accurately capture the social environment within the team throughout the year, the scores of group identification and the group norm of performance were averaged across phases 2, 3 and 4.

Team level measures for conscientiousness, agreeableness, group norm of performance and group identification were created by averaging the scores of each team member's scores within a project team on their respective items. All team level variables had an acceptable level of internal consistency ($\alpha > .80$)

3. Results

An initial inspection of the team level data found no implausible or missing values. Additionally, the relationships between values were considered linear, and the distributions for each variable did not significantly deviate from a standard normal distribution. Two continuous univariate outliers were detected ($p < .001$) and were recoded at 3.29 standard deviations from the mean (Tabachnick and Fidell 2007). No multivariate outliers were detected using Mahalanobis distances ($p < .001$), and missing values analysis revealed that no teams had missing data.

Confirmatory factor analysis (CFA) was used to investigate the conceptual distinction between the group norm of performance and team identification. CFA is a statistical method used to test whether the variance in measured items fits a predetermined model (i.e. a model in which team performance and team identification constitute two distinct variables). As a deductionist procedure, it allows for comparisons between multiple plausible models that could fit the data. How well the data matches the model was assessed through the use of fit indices and relevant criterion values, which were selected based upon their validity, relative consensus in the literature, and ability to measure different aspects of model fit. A model needs to have acceptable fit indices and when comparing two or more models, a model that fits data better (i.e. a model with better fit indices) is accepted as the better model.

Two CFA models were tested: a two-factor model (in which the items for performance norm and team identification loaded onto their respective factors) and a one-factor model (where all items loaded onto a single factor). The following fit indices and their criterion values for good fit were used: standardised root-mean-square residual (SRMR) (Hu and Bentler 1999) and root-mean-square error of approximation (RMSEA) (Browne and Cudeck 1993), with values close to .08 (values that exceed .10 suggest of poor fit), Comparative Fit Index (CFI) and Non-Normed Fit Index (NNFI) with values greater than .90 (Bentler 1992; Bentler and Bonett 1980), and the ratio of chi-squared to degrees of freedom (χ^2/df) with values less than 2 (Bollen and Long 1993). The model that treated performance norm and team identification as separate constructs had all acceptable fit indices ($\chi^2(25) = 39.70$, $p = 0.03$, $\chi^2/\text{df} = 1.9$, CFI = .98, NNFI = .97, SRMR = .074, RMSEA = .09), which were also better than those of the one-factor alternative model ($\chi^2(27) = 159.29$, $p < 0.001$, $\chi^2/\text{df} = 5.90$, CFI = .79, NNFI = .72, SRMR = .89, RMSEA = .25). Accordingly, these results supported that group identification and group norm of performance are distinct, though strongly correlated, constructs ($r = .72$, $p < .001$).

3.1. *Original data*

Partial support was found for hypotheses 1 and 2 that conscientiousness, agreeableness, team identification and team norm of performance would positively influence team performance. The results of the correlational analysis found no significant relationships between any of the hypothesised predictors and team performance. This finding could be attributed to the relatively small sample size of 16 project teams, reducing the power of the tests to detect significant effects (see Table 1).

A standard multiple regression model was used to further test hypotheses 1 and 2. Team performance was regressed against team averages of conscientiousness, agreeableness, team identification, and team norm of performance (see Table 1) to identify if these variables predicted team performance. Team conscientiousness and team identification predicted higher levels of team performance, but team agreeableness and team norm of performance did not. When only taking into account team averages of conscientiousness and team identification, the final model marginally significantly predicted team performance, where higher levels of conscientiousness and team identification predicted higher levels of team performance, $F(4, 11) = 3.13$, $p = .06$, $R^2 = .36$.

Table 1. Correlations between the variables and a multiple regression analysis predicting team performance from the original sample.

Measures	*M*	SD	1	2	3	4	*β*	*sr*
1. Team conscientiousness	3.37	0.56	–				.66*	.55
2. Team agreeableness	3.55	0.52	.44	–			−.37	−.30
3. Team identification	5.40	0.88	−.21	.23	–		.89*	.56
4. Team norm of performance	4.89	0.96	−.13	.32	.77**	–	−.43	−.27
5. Team performance	67.45	4.62	.37	−.02	.34	.05		

Notes: $N = 16$, β = standardised regression coefficient, sr = semi-partial correlation.
*$p < .05$.
**$p < .01$.
***$p < .001$.

3.2. *Simulation analysis*

Underlying many statistical procedures is the assumption of a substantial sample size in order to accurately detect effects and develop models of the data. For data analyses such as correlational and factor analyses, a sample size of at least 200 is required to sufficiently minimise the standard error of correlation (Kline 2000), and to have enough statistical power to detect significant effects (Tabacknick and Fidell 2007). The nature of the current study required close working groups with similar project types and environments. Nevertheless, a large sample with these specific characteristics is difficult, if not impossible to obtain. The limited ability to detect significant relationships with a small sample size has affected previous research into the relationship between the personality of student software engineering teams and the quality of the software they developed (Acuña, Gomez, and Juristo 2009).

Standard data simulation techniques, known as Monte Carlo simulations, were employed to aid in statistical analysis. These techniques have been applied in many fields of research such as physics (Soper 1996), engineering (Bird 1981), statistics (Preacher, Zhang, and Zyphur 2011) and psychology (Cohen and Ross 2009; Komar et al. 2008). Monte Carlo techniques are now being explored in software engineering, for techniques such as life-cycle and risk analyses (e.g. Fairley 1999; Magennis 2012). In software engineering, simulations are used to generate a model of a team or project, and then to calculate possible step-by-step outcomes (Magennis 2012).

Simulation techniques build a model of the sampled data, and compute a larger sample based on those characteristics. Data simulations allow for both the rigour and control of a small study, combined with a large and realistic simulated sample. As a result, the simulated data set will have the strengths of a tightly controlled, real-world sample, without the associated statistical constraints. The literature suggests that in order to apply this technique, the original sample needs to be representative of the population of interest. Given that the current data were collected over two years, members were assigned to groups by academics, and groups were found to be similar and were considered normally distributed, the original sample was determined to accurately capture the natural variation that existed within student software engineering teams in this environment. Repeated sampling should obtain project teams with similar characteristics to the original sample because of the study's design. As a result, the simulation was seen as an accurate representation of a larger sample.

A special case of the Monte Carlo sampling method was employed, where random deviations from a multivariate distribution were computed based on the characteristics of the original data set. A computer script was written for the 'R' statistical package (R Development Core Team 2011) to simulate the original teams data, incorporating an existing simulation script, '.mvtnorm' (Genz et al. 2011). The script treated each of the original project teams as independent populations, and then multivariate normal distributions were created and sampled based on the specific characteristics (means and variance/covariance matrices) of each project team.

The final simulated data set contained 2043 cases, nested in 320 project teams. Simulated team sizes ranged from three to eight members to mirror the original sample, in order to represent repeated sampling under similar conditions. The simulated data were then cleaned and screened based on the same criteria as the original data, by checking that all values were plausible and were normal. One team's data were considered a multivariate outlier, based on Mahalanobis distances ($p < .001$), and were removed (leaving 319 teams). Eighteen groups had their score on a variable recoded at 3.29 standard deviations from the mean, because the distance of the score from the normal curve was large enough to be considered an outlier (Tabachnick and Fidell 2007). Statistical analysis revealed that there were no differences between the original and simulated data for any variable that could not be explained by random deviations ($ps > .67$). All variables had an acceptable level of internal consistency ($\alpha > .78$). Based on these results, the simulated data were considered an accurate representation of the original data.

Table 2. Correlations between the variables and a multiple regression analysis predicting team performance from the simulated data.

Measures	*M*	SD	1	2	3	4	β	*sr*
1. Team conscientiousness	3.39	.35	–				.30***	.28
2. Team agreeableness	3.58	.33	.30**	–			−.24***	−.23
3. Team identification	4.91	.63	−.16**	.14*	–		.44***	.31
4. Team norm of performance	5.44	.54	−.11*	.18**	.70***	–	−.17*	−.12
5. Team performance	67.10	5.16	.17**	−.12*	.23**	.06		

Notes: $N = 319$, β = standardised regression coefficient, sr = semi-partial correlation.
*$p < .05$.
**$p < .01$.
***$p < .001$.

3.3. *Simulated data*

Correlational analysis of the simulated data partially supported hypotheses 1 and 2 that conscientiousness, agreeableness, team identification and team norm of performance would positively influence team performance. Significant positive relationships were found between team averages of conscientiousness, team identification and the measure of team performance. These findings indicate that teams with more conscientiousness members, and teams with more identifying members perform better than teams with low levels of conscientiousness and team identification. Contrary to hypothesis 1, a significant negative relationship was found between team agreeableness and the measure of team performance. These findings indicated that teams with more disagreeable personalities seemed to perform better than teams with more agreeable team members (see Table 2).

A multiple regression analysis was conducted to identify the degree to which team agreeableness, conscientiousness, identification and norm of performance predicted team performance (see Table 2). Mimicking the findings of the correlational analysis, higher levels of team conscientiousness and identification predicted higher levels of team performance, while higher levels of team agreeableness and norm of performance predicted lower levels of team performance, $F(4, 314) = 16.37, p < .001, R^2 = .16$. Team identification made the largest unique contribution to the prediction of team performance, based on semi-partial correlations.

3.4. *Mediation and path analysis*

The results supported hypothesis 3 that team identification would mediate the relationship between team norm of performance and the performance of the team. Mediation analysis served to explore how the team norm of performance affected team performance through a third intermediary or 'mediating' variable (this effect is also known as an indirect effect). Indirect effects were tested using the standard procedure for testing mediation, which involved the Sobel test (Preacher and Hayes 2004), coupled with 99% confidence intervals produced by the bootstrapping technique with 5000 resamplings.

Team norm of performance had a significant positive indirect effect (.27 [.18, .36]), on team performance through its effect on team identification (see Figure 1), $Z_{.05} = 4.81$, $p < .001$. This suggests the group norm of performance has a positive influence on performance, through its positive influence on group identification.

To further investigate the significant relationships found in the previous analyses, all the causal pathways suggested by the previous analyses were incorporated into a path model. To test the full model, the same fit indices and respective criterion values were used as in the previous CFA.

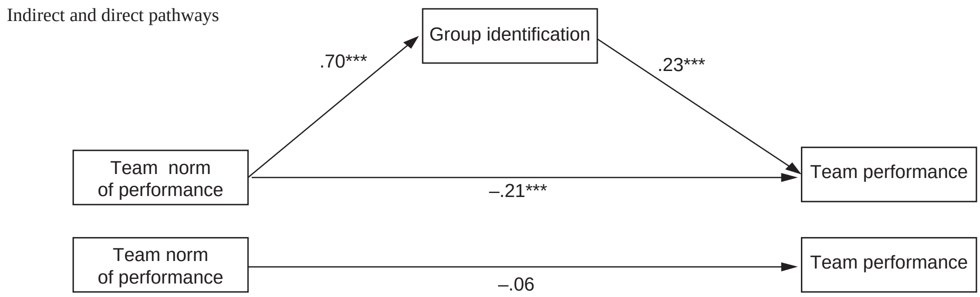

Figure 1. Mediation models showing team identification mediating the relationship between team norm of performance and performance. Presented coefficients are standardised.
* $p < .05$, ** $p < .01$, *** $p < .001$.

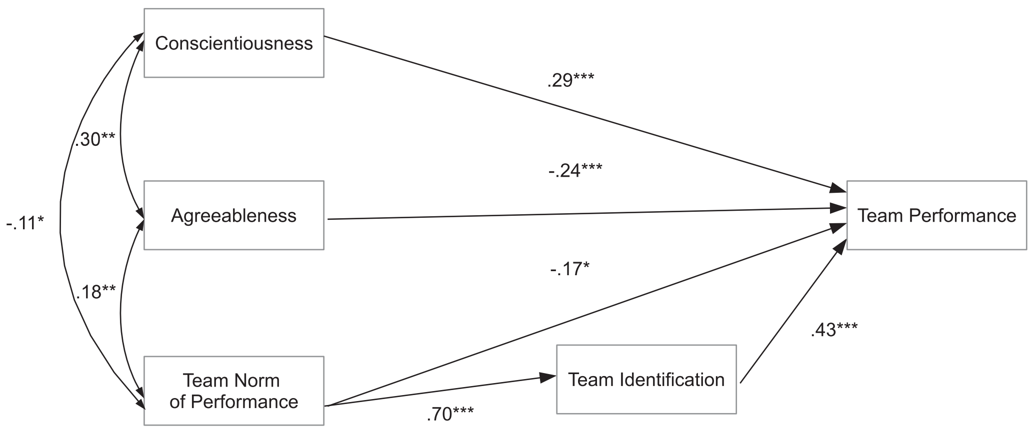

Figure 2. Path diagram showing the relationship between team level measures of conscientiousness, agreeableness, team norm of performance and identification. Presented coefficients are standardised.
* $p < .05$, ** $p < .01$, *** $p < .001$.

The predicted model (see Figure 2) fitted the data well: $\chi^2(2) = 5.54$, $p = .06$, $\chi^2/\mathrm{df} = 2.77$, CFI $= .99$, NNFI $= .98$, SRMR $= .03$, RMSEA $= .07$, $R^2 = .19$.

The final model suggested that when accounting for all predictors, higher levels of team identification and conscientiousness predicted higher levels of team performance, while higher levels of team agreeableness and norm of performance predicted lower levels of team performance. Additionally, team norm of performance was found to have an indirect positive effect on team performance via team identification. It should be noted that there were no other significant pathways or interactions.

4. Discussion

The current study explored the influence of team personality and social identity processes on the performance of student software engineering teams. Although substantial research into these perspectives has been published, there is little research into performance in student software engineering teams and the team as an entity (opposed to the independent contributions of the students within them). The performance of project teams is important, as they are being increasingly emphasised in software engineering curriculums (Denayer et al. 2003; Johns-Boast and Flint 2009, 2013; Lima et al. 2006; Mills and Treagust 2003; Powell 2004). More practically, this study aimed to identify factors that would enable higher levels of performance in future student software engineering project teams and to help educators understand which variables play a substantial role in team performance.

4.1. *The influence of personality*

The results of the current study partially supported hypothesis 1 that team averages of the personality measures of conscientiousness and agreeableness would be positive predictors of team performance. As suggested by the wealth of research conducted into personality and performance (Barrick and Mount 1991; Barrick, Mount, and Judge 2001; Halfhill et al. 2005), team conscientiousness made a significant and unique positive contribution to explaining performance of the student project teams. Contrary to hypothesis 1 and the existing literature, higher levels of team agreeableness were associated with lower levels of performance. Plausibly, higher levels of agreeableness would benefit team performance only if increased positive interpersonal interactions, trustfulness and cooperation directly facilitated performance. The results of the current study clearly showed that in software engineering student project teams, positive interpersonal and teamwork behaviours do not necessarily increase team performance.

The discrepancy between the current results and the literature could be due to the literature's foundation in organisational teams. Highly agreeable student teams may place too much emphasis on interpersonal interactions, cooperation and compromise, and this may impair the team members' ability to work studiously and effectively. Based on the results of the current study, in the context of designing software in student teams, higher levels of performance do not hinge upon highly agreeable and cooperative project team members, but upon the degree to which they are competitive, hard-working and organised. The findings of the current study suggest that average personality of team members is an important factor in the performance of student software engineering teams.

4.2. *The influence of identifying as a team member*

In line with hypothesis 2 that team averages of team identification and team norm of performance would positively influence team performance, higher levels of team identification were associated with higher levels of team performance. Team identification uniquely explained more variance in team performance than team conscientiousness. These results supported the predictions of self-categorisation theory, which suggested that team identification increases motivation to work for the team (Ellemers and Rink 2005). Identifying with and internalising team membership are significant components of team performance.

Higher levels of team norms of performance were associated with lower levels of team performance. This did not support hypothesis 2, and the past research on performance norms (Paulus and Dzindolet 1993; Shih, Pittinsky, and Ambady 1999). Nevertheless, team norm of performance did have a significant positive indirect effect on performance via team identification. These results supported hypothesis 3 that team averages of team identification would mediate the relationship between the team norm of performance and the performance of the project teams. Team norms of performance may predispose students to identify with their project team, which in turn may increase the team performance. Moreover, the results suggest that when students do not identify with their team, increases in the team norm of performance will lead to a decrease in the performance of their project team.

Group identification emerged as a central factor influencing performance in software engineering student teams. The results of the current study suggest that performance norms may foster higher levels of team identification, which in turn increases team performance. This effect could occur through several means. First, teams with higher levels of performance norms are likely to demand more time and input. This increased investment may facilitate team bonding and increase the importance one places on their team membership (Dutton, Dukerich, and Harquail 1994). Second, students may more readily identify with teams that have similar interests to their own. As the student's course mark is governed by the team's assessed performance throughout the year, a high performing team norm could be seen as being more aligned with the goals and values of the respective team members.

Importantly, this suggests that by modifying the perceived norm of performance in student software engineering project teams, team identifications can be influenced and in turn, higher levels of performance can be achieved. Nevertheless, if there is no identification with the team, the norms of team performance on their own do not lead to positive performance. In fact, they lead to more negative team performance. Identifying as members of the team is, therefore, the key to whether the team will or will not adopt the level of performance seen as normative by its members.

5. Limitations and future research

The essential limitation of the study was the sample size, which affected the error associated with the statistical analyses, and the ability to detect statistical effects. Data simulation helped address this issue, but the simulation was based on the characteristics of the original sample. A strength of the current study was the use of real-world project teams, the similarity of data collected over two years, and the absence of any significant differences between the original and simulated sample. However, if biases existed in the original sample, these would reoccur in the simulation. Furthermore, small sample sizes can misrepresent the variability in the population, which would have also been replicated in the simulated sample. Despite these limitations the simulation of the project teams was considered a valid representation of the original sample.

The results of this study suggest a wide range of future research questions. These include: (1) directly measuring the effects of teamwork and its relationship to team performance; (2) exploring team environments in which teamwork facilitates or hinders performance; (3) identifying individual and group factors that strengthen team identification, especially over time (see Bizumic, Reynolds, and Meyers 2012); (4) investigating the degree to which team member enjoyment affects performance; (5) studying whether teams' relative level of performance and teamwork change throughout the lifespan of the project; and (6) exploring how team performance affects student learning. Future research should also vary team composition to investigate in which team environments each type of personality performs best, and if there is a limit to how many teams an individual can identify with over a short period.

To investigate these research questions in more depth, qualitative analysis could be undertaken. Important information about the functioning of project teams could be collected via structured interviews, focus groups and/or surveys, open-ended questions, or through transcripts and video recordings of group meetings and presentations. Qualitative data would allow the study of the dynamics of software engineering project teams that is inaccessible through quantitative means.

6. Summary and conclusions

The results of the current study suggest that team personality significantly influences the performance of student software engineering teams. As personality appears relatively stable and enduring, higher levels of team performance can be achieved through establishing teams with conscientious members, or by providing increased support to less conscientious teams.

Importantly, social identity factors significantly predict performance, over and above, personality trait measures. In the current study higher levels of team norm of performance only led to higher levels of team performance if team members identified as members of that project team.

Fostering higher levels of team identification is essential to increasing performance within software engineering student project teams. Educational environments should foster environments that facilitate team identification, which will in turn influence the performance of the project teams. As a large proportion of the variation in performance remains unaccounted for, future research should explore other factors, such as cognitive ability and subject knowledge, to better understand the performance dynamic of these teams. The present results nevertheless show that engineering educators should focus more on team personality, team norms, and social identification to facilitate higher levels of performance from the student software engineering project teams.

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About the authors

Conal Monaghan finished his undergraduate studies in 2011 and is currently undertaking a PhD in clinical psychology at the Australian National University, Australia. His research interests are related to psychological perspectives on group performance, group membership's effect on behaviour, the public's attitudes towards biotechnology, and how an individual's Machiavellian disposition affects their development and psychopathology.

Boris Bizumic, PhD, is lecturing social and personality psychology at the Australian National University, Australia. His research interests have focused on understanding the relationships between group and individual factors. His work has been published in international journals, including the *European Journal of Social Psychology*, *Political Psychology* and *Applied Psychology: An International Review*.

Kate Reynolds is an expert on group processes and intergroup relations (prejudice and stereotyping, social change, leadership and power). Specifically, she investigates the way in which people's group memberships (others similar to 'us') affect the functioning of the mind (cognition) and attitudes and behaviour. Her work with various students and colleagues is of interest to a range of policy-makers in areas such as educational leadership and school improvement, social norm change in dysfunctional communities, and building social cohesion in the face of ethnic and religious diversity.

Michael Smithson is a Professor in the Department of Psychology at the Australian National University. He is the author of 5 books, co-editor of 2, and author of more than 140 refereed journal articles and book chapters. His primary research interests are decision-making under uncertainty and statistical methods.

Lynette Johns-Boast is a Lecturer in Software Engineering at the Australian National University. Her research interests include learning object repositories and re-usable learning objects, professional education and transfer of knowledge into the workplace, the human aspects of software engineering, including personality and its impact on teams, and women in engineering. She is an active member of the Australasian Association for Engineering Education. She is also a member of Engineers Australia and the IEEE.

Dirk van Rooy is a Lecturer at the Australian National University at the School of Psychology. His research is focused on computational models of social behaviour, including connectionist and multi-agent models. In general, he aims to build theories and models of social cognition that are attentive to the cognitive, social and biological underpinnings of behaviour.