Modelling the Effects of Personality and Temperament in Small Teams

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Mehdi Farhangian
University of Otago

Martin K. Purvis
University of Otago

Bastin Tony Roy Savarimuthu
University of Otago

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Modeling the Effects of Personality on Team Formation in Self-assembly Teams

Mehdi Farhangian(✉), Martin K. Purvis, Maryam Purvis, and Bastin Tony Roy Savarimuthu

Information Science, University of Otago, Dunedin, New Zealand
Mehdi.farhangian@otago.ac.nz

Abstract. Optimizing the performance of teams in modern organizations is an important managerial function, and particularly so in contexts where new teams must continually be formed voluntarily, such as with software development, crowd-sourcing platforms, and even the formation of scientific collaborative teams. In many such cases, team performance is significantly influenced by the makeup of participant personalities and temperaments and goes beyond the analysis of individual skills. In this study, we present a team-assemblage model that is primarily influenced by knowledge of the past performance of team members and their personalities. Our goal is to provide a model, which can be parameterized for specific organizational contexts, for policy makers and managers to assess potential teams formed in dynamic circumstances. To provide real-world validation for our approach, we extracted data from the Python Enhancement Proposal (PEP) process, which involves the repeated self-assembly of software teams from a common pool of developers. We then used agent-based simulation to enact our model with PEP data to predict team grouping formation and resulting team performances.

Keywords: Multi-agent systems · Social Simulation · Personality · Team performance · Team formation

1 Introduction

Clearly the performance of teams cannot be simply predicted as an extension of individual performance and the issue of predicting team performance is becoming more important with today's increased employment of temporary teams [1]. Examples of temporary teams include crowdsourcing platforms, scientific collaboration teams, open source software development teams, and online games. In today's rapidly evolving world, teams are often assembled from a larger network of related people. But there is little understanding concerning how this self-assembly team formation process should be carried out.

In order to understand the mechanisms governing the composition of social groups, Ruef *et al.* [2] conducted a survey and analysed a data set of organizational teams from a sample of the U.S population. They concluded that homophily and network constraints based on strong ties have the most significant influence on group composition.

In addition to such empirical studies, some further studies investigated team assembly mechanisms by using computer simulations. Guimera *et al.* [3] proposed a model for self-assembly in teams based on three parameters: team size, the fraction of newcomers, and the tendency of incumbents to repeat previous collaborations. A team model developed by Johnson *et al.* [4] showed the average tolerance level and attribute range for each population affects individuals' decisions for team coalition.

Since previous collaboration experience is a major factor for self-assembly (as suggested by other researchers i.e. [2]), the model that we present in this paper considers both human factors for group assembly and also knowledge of past performance. In particular, we posit that key human factors arise from personality types, and we consider them in the team-assembly process. Thus, a model is developed on the basis of theoretical and empirical literature on personalities and team behavior. This conceptual model is then implemented as an agent-based computer simulation consisting of simple rules and principles.

Although one might simply posit a model based on the relationship between personality and team performance, the literature in this domain suggests that rules cannot be generalized without considering situational forces such as organizational structure and the types of tasks. Nevertheless, in volatile environments where new teams must be rapidly assembled, some locally-known knowledge must be used to construct the team [11], and this often comes down to local familiarity with past performances and awareness of personality types. We have constructed our model on this basis and have tested it with real-world data from such a team-assembly environment.

The rest of the paper is organized as follows: Section 2 discusses psychological personality models and reviews the literature about the relationship between personality and team performance. Section 3 presents our proposed rules and principles about team-formation mechanisms and our agent-based model. Section 4 is a presentation of some general experiments and results based on our team-formation model. Section 5 is a specification of the model in the domain of small software development teams and serves as both a practical example and a basis for validating the model principles. Section 6 contains the conclusion.

2 Personality

In agent-based modelling, agent personality characterizes agent motivations, behaviour, and thoughts. There have been several simplified schemes developed over the years to profile human personality, the most popular of which seem to be the Five Factor Model (FFM or "Big Five") [5] and the Myer-Briggs Type Indicator (MBTI) scheme [6]. In our work we have employed the MBTI scheme, since (a) it appears to have the most accumulated field data and (b) the FFM model suffers from the disadvantage of identifying and measuring only positive "qualities" of personality. As a consequence, it seems, most people who do not want to be judged are more likely to self-identify their MBTI personality types.

The history of MBTI goes back to Carl Jung, who developed an initial scheme of psychological types that included the notion of introversion and extraversion [7]. Myers added additional elements to this arrangement, and it has evolved into the MBTI scheme [8], which has four "dimensions" of human personality: **Extraversion** vs. **Introversion** (where people focus their attentions)**, iNtuition** vs. **Sensing** (the way that people gather information)**, Thinking** vs. **Feeling** (the way that people make decisions) **Judgmental** vs. **Perceptive** (the way that people deal with the outer world). The 16 possible type combinations are typically referred to by an abbreviation of four letters—the initial letters of each of their four type preferences. For instance: ISFJ represents introversion (I), sensing (S), feeling (F), and judgmental (J).

In our model, a number between 0 and 100 indicates the personality of agents in each dimension. For example for the Extraversion-Introversion (EI) dimension, a value between 0 and 50 means that a person is extraverted, and a value between 50 and 100 means s/he is introverted.

2.1 Personality and Team Performance

There is interest in evaluating how personality affects team performance, but we recognize that understanding human personality and its effects on performance are enormous subjects in themselves, and we do not pretend to treat this subject in all its depths here. Nevertheless, there are some commonly held notions concerning variations of human temperament and personality that have been developed over the past century, and we take advantage of some of them.

During task activities, the team's personality composition strongly influences the success in finishing a task. Tziner [9] mentioned two social psychological perspectives that account for how team composition affects performance:

- *Similarity theory* predicts that homogeneous teams will be more productive because of the mutual compatibility of the members.
- *Equity theory* predicts team performance is higher in heterogeneous groups because of complementarity among members.

In order to model this aspect of team performance, we introduce two indicators [10] that are used in conjunction with the MBTI measures:

- Team Personality Diversity **(TPD)**: the variance with respect to a particular personality trait among team members.
- Team Personality Elevation (**TPE**): a team's mean level for a particular personality trait.

For both similarity and equity theory, TPD, which measures team heterogeneity and homogeneity, is significant. Teams generally high in terms of TPD are described as heterogeneous, whereas teams that are low in terms of TPD are homogeneous. Research findings regarding the relationship between TPD and group effectiveness are mixed. Different tasks have different requirements, for instance, some may require a high level of cognition and complex thinking, while some others may require a high degree of coordination and teamwork. In our environment, we considered two types of tasks:

- *Structured* – tasks that are straightforward and do not require planning.
- *Open-ended* (or 'cognitive') – tasks that require more creativity and imagination (for example, surveying tasks and finding suitable strategies).

Wiersema and Bantel [11], noting that team homogeneity brings about a shared language among team members and improves integration and communication frequency, suggested homogeneous teams are likely to perform better on tasks that require high coordination. In contrast, Bantel [12] predicted that homogeneous teams would perform poorly (because of lack of openness) on tasks requiring new resources of information, and they recommended heterogeneous teams for tasks that require a high level of creativity.

Thus, we know that TPD and TPE do not uniquely predict team performance, but based on the literature discussed above, we assume that for structured tasks low TPDis likely to have a positive effect on team performance. For open-ended tasks, high TPD is likely to positively affect team performance.

3 Proposed Team formation mechanism

In order to develop principles and rules of our agent-based model, we made the following assumptions based on the literature on MBTI personality (i.e. [13]).

iNtuition-Sensing. We assume that intuitive types are more likely to record their past experiences about team performance.

Thinking-Feeling. In our model it is assumed feelers choose new team members based on their familiarity with them, rather than for logical reasons such as experience.

Judging-Perceiving, We assume team members with judging personalities are more likely to refrain from changing their team and prefer to continue with the existing team, while employees with perceiving personalities are more flexible and more likely to change their teammates.

Extraversion-Introversion, We assume employees with extraverted personalities connect with more people in their social network.

In our team formation mechanism, two types of people are involved, which we call requesters and contributors. Requesters start a project and, seeking collaborators from sources such as crowdsourcing platforms, attempt to recruit the required people and complete the work for projects. Contributors are the recruited people who contribute to the tasks. The personality of requesters and contributors determine their team's overall behavior.

To form teams, we proposed a first-price auction-based algorithm, comprising requester and contributor agents. In this system, a virtual currency is assigned to both requesters and contributors. Both of them try to be part of a team that gives the highest chance to increase their wealth in this virtual currency. Their performance in the task is presented in Formula 1:

$$v_{ij}(t) = Performance_b + v_{ij}(t-1) \quad (1)$$

v_{ij} indicates the value that agent i assigns to agent j after performing a task, and $Performance_b$ indicates the performance of the team in task b and presented in Formula 2.

$$Performance_b = 100 - |Heterogeneity_{\,l} - Tasktype_{\,b}| \quad (2)$$

where $Heterogeinity_{\,l}$ indicates the heterogeneity of team l and is calculated based on the average of the standard deviation in each personality dimension and presented in Formula 3. $Tasktype_{\,b}$ is the nature of task b that shows the level of how open-ended and structured the task is and can be a number between 0 and 50. 0 indicates that the task is extremely structured, while 50 indicates the task is extremely open-ended. $\overline{S_{EI,J}}$, $\overline{S_{NS,l}}$, $\overline{S_{JP,l}}$ and $\overline{S_{TF,l}}$ represent the standard deviation of team l in Extraverted/Introverted (E-I), iNtutive/Sensing (N-S), Thinking/Feeling (T-F) and Judging/Perceiving (J-P), respectively.

$$Heterogeneity_{\,l} = \frac{\overline{S_{EI,l}} + \overline{S_{NS,l}} + \overline{S_{JP,l}} + \overline{S_{TF,l}}}{4} \quad (3)$$

In the agent model, an agent's individual decision about team formation is determined based on two factors: Past success and Familiarity.

- ***Past success***: the history of previous team performance.
- ***Familiarity****:* the history of social interaction of agents.

As mentioned in the assumptions in Section 3, past-success is a more important factor for people with sensing personality, and familiarity is a more important factor for people with feeling personality. So requester j offers C_{ji} to the contributor i as presented in Formula 4.

$$C_{ji} = \frac{(NS_j * v_{ji} + TF_j * familarity_{ji})}{NS_j + TF_j} \quad (4)$$

In this formula, NS_j is the sensing-intuition personality of the requester j. TF_j is the thinking-feeling personality dimension of the requester j, and $familarity_{ji}$ represents the interaction of agent j with agent i and is calculated as Formula 5, where G_k improves whenever agent j interacts with agent i as presented in Formula 6.

$$familarity_{ji} = 10 * e^{G_{kji}} \quad (5)$$

$$e^{G_{kji}} = e^{G_{(k-1)ji}} + 0.1 \quad (6)$$

When contributors receive bids, they select the requester with the highest expected payoff. A_{ij} indicates the payoff of contributor i by joining team j and is presented in Formula 7.

$$A_{ij} = \frac{NS_i * v_{ij} + TF_i * familarity_{ij}}{NS_i + TF_i} + C_{ji} \quad (7)$$

Apart from performing a task, agents interact with each other. The probability of interaction is based on the extent to which they have an extraverted personality and the probability of leaving a team or firing a contributor is related to the Judging personality index of agents .

4 Experiments and Results

Experiments have been conducted using NetLogo. In the initial settings, agents represent requesters and contributors. Four numbers between 0 and 100 are randomly assigned to each personality dimension for each agent. A number between 0 and 50 represents the degree of a task's being structured or open-ended. The number of required contributors for each task is a random number between 2 and 4. In each time step, new tasks are added to the environment, and the simulation is terminated after 100-time steps. To account foro the randomness of the assigned values, performances are reported as averages over 100 simulation runs.

We were interested in investigating the most popular team compositions. To explore this further, from our simulation data, we added labels to the variables about team personality, such as TPD-EI, TPD-NS, TPD-TF, TPD-JP, TPE-EI, TPE-NS, TPE-TF, TPE-JP, as "Very Low", "Low", "Medium", "High", and "Very High". Observations are summarized in Figure 1. These results will be further discussed and compared in the validation section, where we compare them with the particular domain presented in the next section.

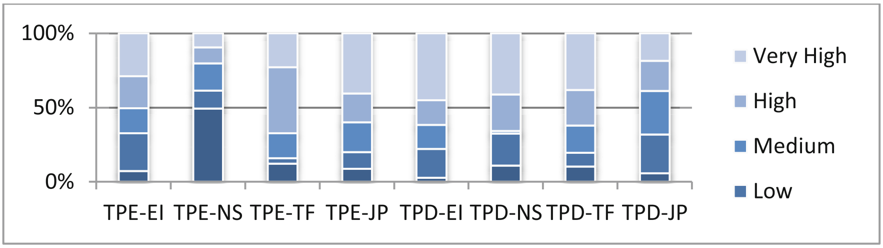

Fig. 1. Team composition (for open-ended tasks)

5 Validation

our model and simulation represent a considerable simplification, and its usefulness needs to be validated with real data. As we mentioned earlier, generating general rules that determine the relationship between team performance and personality is not straightforward. Nevertheless, some further validation would be valuable, and this is always an issue with agent-based modelling. Some researchers have suggested that data mining techniques applied to real projects can be useful in this regard (e.g. [14]). To pursue this idea, we have chosen a specific application domain and investigated a real case study by extracting data from the Python Enhancement Proposal (PEP) process.

A PEP is a document that describes a new feature to be developed by a small team for Python, for which developers use mailing lists as the primary forum for discussion about the Python language's development. We obtained access to 363 PEPs categorized into three labelled categories: process, information, and standard track. There are temporary teams associated with each PEP, where certain team members work together for one task but may change the team for another task.

We are primarily interested to find useful information to show the relationship between personality and performance of teams of developers. In order to identify the personality of developers, some steps were required. Using similar methods as [15], we developed a formula to determine the personality of people from their texts. Initially, the data was extracted from three social networking websites (Quora.com, Reddit.com, and Collegeconfidential.com) where people self-reported their MBTI personalities. After extracting data and texts of 228 users in Quora, we employed the Linguistic Inquiry and Word Count LIWC tool [16] to analyze each textual fragment. After generating the value of all the variables in our Quora samples, we used Pearson correlation to find correlations between personality and these variables, and we considered the variable combinations having their correlation at the 0.01 level to be significant. These correlations were then cross-tested against 25 users in Reddit and 135 users in College Confidential, and they were shown to be 65% and 73% accurate. We then applied our proposed formula to determine the personality of Python developers based on their own texts that were publicly available on the Internet.

After determining the personalities of the developers in the four dimensions, we calculated the TPE and TPD in each dimension and labeled them in a similar way to the previous experiments.

Bayesian theory was adopted for our computational model to predict the probability of success based on TPE and TPD in each dimension. We employed the WEKA machine learning software tool to generate and test the Naïve Bayes model on the PEPs data. By using the NaiveBayesSimple algorithm, the probability of each condition is computed. Based on these probabilities, we can estimate the probability of success in each task based on team composition personality.

New experiments were developed and the roles of requester and contributor were assigned to agents randomly. For each round, agents update their beliefs about success and familiarity with other agents based on their sensing and feeling personalities, respectively. The decision about changing the team is related to the perceiving personality. However, unlike the previous experiments, the performance of each team is not determined by Formula 2. Instead, the performance is determined by the conditional probabilities calculated from data extracted from the PEPs. In summary, apart from the performance calculation, other settings are similar to the previous experiments.

Our interest is to determine the most popular team composition. We assume the nature of tasks in software development is more open-ended and that a higher degree of collaboration is required. The most basic validation is comparing the results about the team composition in the open-ended tasks (Figure 1) and the new results which are summarized in Figure 2.

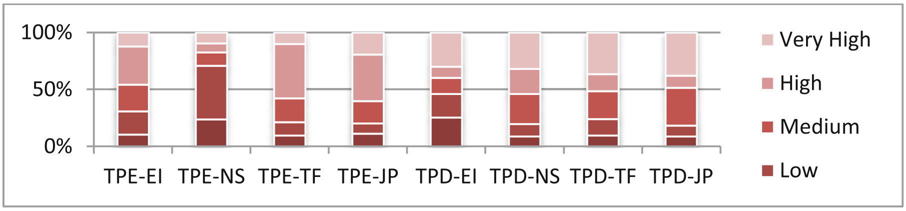

Fig. 2. The composition with data extracted from performance in PEPs

The data shows our model's ability to generate context-dependent behavior. The results show the frequency of team composition in the simulation with open-ended tasks corresponds very well with the simulation results when performance is derived from PEPs. Comparison of Figure 1 and Figure 2 reveals most cases have similar trends, and teams have evolved similarly. If only the comparison of "High" and "Low" is considered as the main criterion, we observe that the model predicts 7 (all variables in the team composition apart from TPD-EI) out of 8 variables correctly and has 87.5 % accuracy. This demonstrates that our model can be used to predict future team formation where teams are formed on a temporary basis.

6 Conclusion

The modeling approach outlined in this research can be used for researchers to have a better understanding about the mechanisms behind the team-formation process. In addition, it can be of use to policy makers whose aim is discovering the most efficient team composition to perform certain types of tasks. We argue that there is no universally successful personality configuration, and success is often significantly related to contextual forces.

We applied our model to a specific domain (PEPs). We determine the personalities of software developers in PEPs. Finally, based on these relationships and employing Bayesian theory, we extracted data about the probability of success in various team composition conditions. We then ran a new set of experiments based on the data extracted from the PEPs. The new results present some similarities with the previous experiments. The observations from two sets of experiments were similar in term of teams' evolutions. These results show the ability of the proposed model in team-formation prediction.

Further experiments and validations must be performed before our results can be generalized. We thus encourage the execution of similar studies of other globally distributed teams to validate our outcomes.

References

1. Contractor, N.: Some assembly required: leveraging Web science to understand and enable team assembly. Philos. Trans. A. Math. Phys. Eng. Sci. **371**(1987), 20120385 (2013)
2. Ruef, M., Aldrich, H., Carter, N.: The structure of founding teams: Homophily, strong ties, and isolation among US entrepreneurs. Am. Sociol. Rev. (2003)

3. Guimerà, R., Uzzi, B., Spiro, J., Amaral, L.A.N.: Team assembly mechanisms determine collaboration network structure and team performance. Science **308**(5722), 697–702 (2005)
4. Johnson, N., Xu, C., Zhao, Z., Ducheneaut, N., Yee, N., Tita, G., Hui, P.: Human group formation in online guilds and offline gangs driven by a common team dynamic. Phys. Rev. E **79**(6), 066117 (2009)
5. Costa, R.R.M., Paul, T.: Professional manual: revised NEO personality inventory (NEO-PI-R) and NEO five-factor inventory (NEO-FFI). Odessa, FL Psychol. Assess. Resour. (1992)
6. Myers, I.: The myers-briggs type indicator. Consult. Psychol. Press (1962)
7. Jung, C.G.: Psychological types: or the psychology of individuation. Harcourt, Brace (1921)
8. Myers, I.B., McCaulley, M.H., Most, R.: Manual: A guide to the development and use of the Myers-Briggs Type Indicator. Consult. Psychol. Press (1985)
9. Tziner, A.: How Team Composition Affects Task Performance: Some Theoretical Insights. Psychol. Rep. **57**(3f), 1111–1119 (1985)
10. Neuman, G.A., Wagner, S.H., Christiansen, N.D.: The Relationship between Work-Team Personality Composition and the Job Performance of Teams. Gr. Organ. Manag. **24**(1), 28–45 (1999)
11. Wiersema, M., Bantel, K.: Top management team demography and corporate strategic change. Acad. Manag. J. (1992)
12. Bantel, K.: Strategic Planning Openness The Role of Top Team Demography. Gr. Organ. Manag. (1994)
13. Bradley, J.H., Hebert, F.J.: The effect of personality type on team performance. J. Manag. Dev. **16**(5), 337–353 (1997)
14. Remondino, M., Correndo, G.: Data mining applied to agent based simulation. In: Proceedings of the 19th European Conference on Modelling and Simulation, Riga, Latvia (2005)
15. Rigby, P., Hassan, A.: What can oss mailing lists tell us? a preliminary psychometric text analysis of the apache developer mailing list. In: Fourth International Workshop on Mining Software Repositories (MSR 2007: ICSE Workshops 2007), pp. 23–23 (2007)
16. Pennebaker, J.: Linguistic inquiry and word count: LIWC 2001. Mahway: Lawrence Erlbaum Associates, p. 71 (2001)