CAPTURING THE EFFECT OF PERSONALITY ON TEAMS WITH AGENT-BASED MODELLING

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Abstract

Continuing advances in information and communication technology (ICT) have changed the landscape of project management. Now there are increasing occurrences of short-term projects staffed by ad hoc assemblies of temporary team members who have been quickly recruited from a candidate population. However, there is little in the way of general guidelines available concerning how to manage these volatile situations. In particular there are no established approaches for more effective assembly of ad hoc project teams with respect to the collective psychological makeup of the team members. This thesis makes a contribution in this area by providing an examination into improved ways of assembling ad hoc project teams with respect to the psychological (personality) profiles of team members in order to produce more effective project outcomes.

This thesis is divided into three main sections. In the first section, we investigate how the strategies that determine the composition of teams can affect team performance. Because of the autonomous nature of team members, we employ agent-based modelling techniques that can be used to predict the assembly of teams and their ensuing performance. Our agent-based simulations in the first section of this thesis demonstrate emergent effects based on different parametrisations. In order to compare the outcomes of these models with real-world situations, a practical method of simply determining individual personality types is needed. In this regard, we have used the Myers-Briggs Type Indicator (MBTI) index to identify personalities.

In the second part of the thesis, we develop a team formation model to explain how self-assembly teams tend to evolve in the area of software development. In order to develop an agent-based model intended to predict the teams' compositions, we describe our assumptions about the factors affecting team formation. A model is developed to explain the mechanism behind team formation and the extent to which our assumptions can predict the compositions of teams. Our model has been validated against a case study known as the "Python Enhancement Proposal" (PEP), which is used by small ad-hoc software teams to enhance the Python programming language. In order to discover the personality of a PEPs developer, we make an additional contribution in this thesis: that is, developing a novel model that infers the MBTI specification of personality from the candidate team members' writing styles. By comparing PEPs data with the results produced from our agent-based simulations, we can identify the factors that explain the mechanisms behind team formation. In this study, we

identified four significant input factors that affect team composition and performance: *previous performance*, *teammate familiarity*, *MBTI Feeling personality*, and *MBTI Perceiving personality*.

The third part of this thesis focuses on the relationships between the personalities of a team and the team's group performance. We introduced a data-driven methodology that can be customised for different organisations to discover the relationship between personality and team performance. In addition, we identified the team compositions that can result in better performance. One hypothesis that was tested and confirmed in this connection is the positive effect of personality heterogeneity on the performance of software development teams.

The thesis makes several methodological and practical contributions. In this thesis, not only have we developed and tested how people *do* form into a team, but also we investigate how people *should* form into a team. The models and techniques developed in this thesis can be used to guide and help managers to investigate the assembly and evolution of temporary ad-hoc work teams. Managers can apply these models in connection with conducting various "what-if" analyses by simulating the behaviour of teams under different circumstances.

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INTRODUCTION

The behaviour of teams is of interest to researchers in different disciplines. Due to advances in the telecommunication industry, the nature of teams is changing; teams are more temporary and their composition is evolving over time (Contractor, 2013). This new nature, and how an agent-based modelling approach can show the collective team performance effects of individual team-members' attributes are the main focuses of this thesis. In particular, in this thesis, the effect that different combinations of distinct personality types can have on team self-assembly and team performance has been investigated.

This chapter provides an overview of the proposed research. Section 1.1 presents the motivation behind the research and its problem statement. Section 1.2 describes the research objectives. Finally, Section 1.3 provides an outline of the remaining chapters of the thesis.

1.1 Motivation

Teamwork modelling is an approach for studying team formation and team dynamics and it is essential for project planning, training employees, supporting employees in making decisions, and in supporting managers' decision-making on task allocations (Fan & Yen, 2004).

In today's rapidly evolving world, teams are often assembled from a larger network of related people. Examples of these temporary teams include crowd-sourcing platform contributors, scientific collaboration teams, open-source software development teams, and online games development teams. However, there is little understanding concerning how this self-assembly team formation process should be carried out and how team performance plays a role in team composition and vice versa (Contractor, 2013).

Most contemporary organisations require individuals to work as a part of a team; hence teamwork has become an important area of study among researchers (Driskell et al., 2006). It is widely accepted that project teams in modern human activity are often self-assembling, and the members of these teams have a degree of autonomy in selecting their teammates, rather than being directed into teams (Wax, 2015). Team dynamics cannot be fully discussed without considering two factors, which are *predicting teams' makeups* and *teams' performances*. Nevertheless, the mechanism behind the project team makeup has received less academic attention (Contractor, 2013). Many project teams today consist of some ad-hoc members who collaborate with each other only for the duration of a project. With the advance of telecommunication, the importance and frequency of these ad-hoc teams has increased. Therefore, this thesis aims to improve our understanding about measuring team performance and its effect on predicting the composition of ad-hoc teams. Various factors affect this team behaviour, such as skill, knowledge, and demographic characteristics. Although these factors are important, personality is especially crucial, and it has not been fully covered in prior studies. There is little understanding about how personality plays a role in formation of the self-assembly teams (Wax, 2015). As a result, in this thesis, particularly, we investigate the role of personality in analysing team behaviour.

The social phenomena in teams that shape their performance and composition often occur in connection with repeated interactions between individuals over time, and as we will explain in the next chapters, we argue that agent-based modelling is the best approach for contributing to a detailed understanding of such dynamics and interactive processes. So in this thesis, agent-based techniques have been employed to model team formation and assess team performance in order to explore the factors that affect team behaviour and to conduct different "what-if" analyses to investigate the magnitude of these factors.

The personalities of team members often affect how they engage in certain types of team behaviour, such as selecting a team member or reacting to a request for help. The effect that different combinations of distinct personality types, which is hypothesized to be a significant factor, has on team formation and team performance has not been investigated. In order to compare the outcomes of these models with real-world situations, a practical method of simply determining individual personality types is needed. In this regard, we have used the Myers-Briggs Type Indicator (MBTI) (Myers et al., 1985) index to identify personalities and our own, original text-mining technique that can be used to extract MBTI personalities from the texts written by prospective team members.

The MBTI classifies people based on their personality tendencies into four categorical dimensions:

1. **Extraversion/Introversion** reflects the way people focus their attention. Extraverted people focus their attention on the outer world, while Introverted types prefer quiet reflection and privacy and focus their attention on the inner world.

2. **Sensing/iNtuition** reflects the way that people take in information. Intuitive types perceive their environments with an emphasis placed on meaning and associations; while Sensing types perceive their environments with an emphasis on detailed and sequential observations.
3. **Thinking/Feeling** reflects the way that people make decisions. Thinking types follow logical principles, while Feeling types emphasize the consequences of their decisions on other people.
4. **Judging/Perceiving** reflects the way that people deal with ongoing task complexity. Judging types will be motivated to complete assignments in order to gain closure. In contrast, Perceiving types prefer an open flexible learning environment, in which they are continually stimulated by new and exciting ideas

More details about MBTI are elaborated in Chapter 2. In this thesis, we used agent-based modelling for demonstrating how people *do* form into a team and how they *should* form into a team. Because of the volatility of changing circumstances and local contexts, self-assembly of these teams is often essential – only the local participants know the local context and are more likely to have a better-informed understanding of who should form the team (Zhu et al., 2013). Therefore, voluntary participation based on shared interests and goals is inevitable. Thus the members of such teams have a degree of autonomy in choosing their fellow team members. Self-assembly in teams is a social behaviour with a considerable effect on the huge number of today's team projects, such as open-source software development teams.

We hypothesize that understanding the mechanism behind team formation helps us to improve our understanding and managing team performance. To test our hypotheses, in the first part of this thesis, three models are presented to investigate how the performance of a team is directly influenced by the strategies that are chosen for team member selection. In the first model, software development environments are selected in which individuals are assigned to teams by a manager. The second model analyses the collaborative learning environment in which teams are self-assembled (although their freedom in choosing a team member is limited because they rely highly on the knowledge and skills of team members). In the third model, a game-playing environment is analysed in which team formation is fully autonomous and team members can decide freely about their teams and team members. The contribution of this part of the thesis focuses not so much on the specific simulation results, but on developing a modelling and simulation approach that can predict interesting emergent effects based on MBTI parameterizations.

We hypothesised that some personality-related factors can explain the evolution of the team composition of self-assembly teams. We tested these hypotheses on engineering teams engaged in the development of Python language Enhancement Proposals (PEPs).

Moreover, we hypothesize that personality can be inferred from text style. Since we do not have access to the personality of PEPs developers (and soliciting this information is impractical), this thesis also contributes to developing a computational model that determines the personalities of people based on their writing styles.

The main hypotheses we have employed in this thesis are summarized in Table 1.1 at the end of this chapter

1.2 Research Objectives

This thesis intends to determine the extent to which an analysis of the personalities of team members can be used to predict their team performance and team composition. In connection with this intention, the work presented in this thesis employs agent-based modelling (Macal et al., 2005) of teamwork. The main research question that this thesis attempts to answer is:

How does human personality affect the way self-assembly teams form and evolve over time?

We are mainly interested in understanding the mechanism behind evolution of the composition of temporary teams.

To be able to solve this challenge, this thesis will:

- Demonstrate the relationship between ad-hoc team formation and team performance. To do that, an agent-based modelling approach is employed.
- Demonstrate the usage of the Myers-Briggs Type Indicator (MBTI) personality test in team modelling. The MBTI index is taken to be the main indicator of agent personality.

- Develop an ad-hoc-team formation model. We hypothesize that some personality-related factors determine the decisions of individuals for shaping and reshaping a team.
- Demonstrate the usefulness of the team formation model. In other words, the developed team formation model is tested against some empirical data.

In summary, this thesis contributes to improve understanding in this area by using computer simulation to (a) explore the effects of personality on team formation and team performance and consequently to (b) demonstrate how self-assembly teams evolve over time.

1.3 Thesis Outline

This thesis argues that team performance and prediction of team composition are two essential aspects for developing a team model. In this connection, this thesis covers two story lines systematically. In the first storyline, we develop a model for predicting the composition of self-assembly teams. To demonstrate the usability of this model, a real case study from Python Enhancement Proposals (PEPs) (Rossum et al., 2000) is selected and various hypotheses in the team formation model are tested against real data.

In addition to predicting the *composition of self-assembly teams*, which is explained in the first storyline, predicting *team performance* is the centre of attention for the second storyline. Throughout the thesis, we discuss how these two storylines are related to each other and how understanding team performance is a vital factor for prediction of the team composition in self-assembly teams.

In this connection, we incorporate personality in ad-hoc team modelling and we develop a flexible and reusable model for predicting team composition on team performance. For this purpose, the agent-based modelling paradigm has been chosen as the most promising approach. This thesis contains 12 chapters that can be categorised into six main topics:

1. Introduction and literature review (Chapter 1 and 2).
2. Modelling the effect of team formation mechanism and personality on team performance (Chapters 3,4,5, and 6).

3. Modelling how self-assembly teams evolve over time in software projects (Chapter 7).
4. Demonstrate the relationship between personality of teams and their performance (Chapters 3, 5, and 11).
5. Case study and validation of the developed model in Chapter 7 (Chapters 8, 9, 10, and 11).
6. Discussion and conclusion (Chapter 12).

The two storylines of the thesis, which are team formation and team performance, will arrive at the practical conclusions and implications resulting from this thesis that can be implemented in a decision support system. The remainder of this thesis has been organised in the following way.

Chapter 2

This chapter evaluates and summarises past research on team formation, team performance, and other key concepts that are used in this thesis and identifies gaps in the research. This chapter includes three main parts. The first part is an overview of team modelling. It describes the assumptions that need to be taken into consideration for modelling the behaviour of self-assembly teams. Two main components of team modelling in this thesis, which are team composition and team performance, are the focus of this part. Moreover, it presents personality as a key factor that determines human behaviour in the teams. Furthermore, it reviews the effect of personality on team performance.

Since individuals in self-assembly teams have a degree of autonomy, agent-based modelling is considered to be a suitable paradigm for the basis of our team modelling approach. Therefore the second part of this chapter reviews the agent-based modelling of teams, followed by a review of the usage of personality in agent-based modelling.

One of the cornerstones of this thesis is the relationship between text usage and personality, which is reviewed in the third part of this chapter. In order to empirically test our self-assembly model, we need a mechanism that infers personalities from written texts. As a result, this part examines the previous studies conducted in this domain and their limitations for use.

Chapter 3

This chapter examines the impact of team formation mechanisms and team performance in an environment in which teams are allocated to tasks by a manager. To examine the importance of team formation, a framework for team modelling is proposed. The result of our agent-based simulation demonstrates how team formation mechanisms can play a role in team performance.

Usually, past team performance is considered as a key factor in understanding teams. We admit this factor is important, however, in order to have an integrated team modelling approach; the team formation mechanism should also be investigated.

Moreover, we are interested in exploring the use of personality in team modelling. This chapter improves our understanding of models that incorporate personality as measured in terms of MBTI categories in predicting team behaviour. In order to promote this understanding and analyse the effect of predicting team composition in team performance, we develop a team formation model. In this model, which is in the area of *software development*, teams are formed by managerial decision rather than being self-assembly. By reviewing previous findings from MBTI analysis and Belbin Team Roles (Belbin, 2004), we develop a computational model to measure the performance of teams.

In our experiments conducted using the model, we are interested in analyzing team formation mechanisms and their effects on team performance in a dynamic environment. Based on these experiments, we develop a set of propositions about the conditions under which there are, and are not, performance benefits from employing a particular strategy for team formation. We argue that team formation strategy should be customized based on the level of dynamism and distribution of personality among employees.

Chapter 4

Here we develop a model about collaborative learning of knowledge and skill. In order to understand the effect of team formation mechanisms on collaborative learning and consequently team performance, we develop a model of collaborative *learning* in project teams. We also develop a modifiable template for the examination of the influences of growth of knowledge and skill on individual and team performance via simulation experiments. In our model, people spread their knowledge by communicating with each other. Deciding to share knowledge and accepting knowledge depends on the trust of the teammates.

In our agent-based model, we investigate how people may grow their knowledge and skill via two different team formation mechanisms, which are team formation based on trust and team formation based on skill. The results show the impact of the team formation mechanism on collaborative learning and team performance.

Chapter 5

In order to demonstrate the effect of team formation on team performance for situations in which the team members have complete autonomy, we investigate in this chapter the role of personality in influencing teams' performance while *playing team games*. In order to deal with the ambiguity and subjectivity of human behaviour in the teams, we used a fuzzy-logic-based MBTI parameterization of player personality. Experiments employing agent-based simulation are then presented which show the effects of various combinations of personality and temperament types on team performance in the context of competing team profiles. We can conclude from the results that personalities of players, which are a key factor that determine their team formation strategy, affect their team performance.

Chapter 6

In Chapters 3, 4, and 5, we presented three models that demonstrate the role that incorporating team formation mechanism can play in generating improved team performance and in this chapter we discuss how these models can be used in a decision support framework for researchers, managers and website designers.

Chapter 7

Chapters 3, 4, 5, and 6 demonstrate how previous team formation affects team performance. In this connection, Chapter 7 provides a model for team assembly by incorporating the personality as measured by MBTI test. Similar to the models in Chapter 5, the behaviours of the agents are regarded as being determined by their personalities. We hypothesize that two main factors are involved when an agent chooses to be in a team with another agent. The first factor is the agent's experience of the previous performances of the other agents, and the second factor is the familiarity these agents have with their potential team members.

Moreover, some other hypothesised factors that can influence team behaviour are considered in this chapter, including one concerning of relationship between team performance and personality.

In the experiments using agent-based simulation, two types of tasks are used; open-ended tasks and structured tasks. The relationship between team performance and the personality of the team cannot be formulated without considering the type of task. The model developed in this chapter is a key element of the main argument of this thesis, and this model is empirically tested (details are presented in Chapters 9 and 10).

Chapter 8

In order to understand the usability of the team-assembly model presented in Chapter 7, the key data of a real case study are collected. We have chosen a specific application domain, which is the Python Enhancement Proposal (PEP) process. PEPs are the main means for Python designers to propose new features, to collect community input on an issue, and to document design decisions. PEPs are created by self-assembled teams (with independence over the process of team formation). Because we do not have direct access to the personality identifications of the PEPs developers themselves, a mechanism for inferring their personalities is needed. As a consequence, the chapter also has contributed in developing a computational model that identifies the personality of people based on their writing styles.

To predict Myer-Briggs Type Indicator (MBTI) types of users from their writing styles, text written by users on three social networking websites (Quora, College Confidential, and Reddit) were gathered, and the correlations between Linguistic Inquiry and Word Count (LIWC) (Pennebaker, et al., 2001) dimensions and MBTI personalities were analysed. By this analysis, we established a model that infers personality types based on a person's textual style. Using this model, we infer the personality types of developers in Python Enhancement Proposal (PEP) processes. In summary, this chapter provides three contributions:

a) Provides insight about the personality distribution among social networks of developers.

b) Develops a computational model to determine the relationship between a person's MBTI-specified personality and his or her linguistic style.

c) Infers the personality types of PEPs developers.

Chapter 9

This chapter focuses on one of the hypotheses in Chapter 7, which is the relationship between team performance and personality by analysing the data extracted from PEPs. It tests one of our hypotheses in our proposed self-assembly model that heterogeneity in the personalities of team members improves teams' efficiency. Bayesian theory is adopted here for our computational model to predict the probability of success based on the personality of team composition. The results indicate that heterogeneous teams positively affect the performance of software project teams.

Chapter 10

This chapter investigates hypotheses presented in Chapter 4 about team assembly. The main research question of this chapter is *to what extent do those hypotheses explain the team composition in the PEPs data*? In order to evaluate our model, a cross-validation procedure was used. Moreover, a Pearson correlation was used to examine the contributions of our hypotheses in the prediction of team-assembly.

A combination of some hypotheses helped us to correctly predict some team compositions in the PEPs. This highlighted the potential of using simulation for predicting team composition. The results of different combinations of our hypotheses were compared to examine the reliability and influence of these hypotheses. The main factors that positively impacted the accuracy of our proposed model were:

1. Those agents' personalities positively associated with the increase of likelihood of changing teams.
2. The familiarity of agents with other teammates.
3. The personalities of agents associated with the importance of familiarity for teammate selection.
4. The personalities of agents associated with the importance of previous performances.

In the main model presented in this chapter, the influences of familiarity and previous performance are weighted equally. In order to evaluate the relative importance of these factors, more experiments were conducted where the relative weights were modified.

Chapter 11

In Chapter 9, the role of heterogeneity in team performance is explored. However, more detailed analysis about the relationship between team performance and personality can be insightful. This chapter presents a decision-support model that can assist software team managers to form teams that are more likely to have more appropriate personality combinations of team members. In order to generate rules reflecting the relationship between team personality and performance, we analyzed the collected dataset by using an association rule-mining technique. Most of our findings are supported by various empirical studies in the literature. In general, these rules suggest that managers may achieve enhanced team outcomes by choosing team groups that are (a) generally MBTI-based Introverted, Judging, Feeling, and Intuition-oriented, or (b) are heterogeneous, especially in terms of cognitive style (with respect to the Intuition-Sensing MBTI dimension and the Judging-Perceiving MBTI dimension).

Chapter 12

The final chapter returns to the thesis problem statement and the objectives posed, and shows how these problems have been resolved and the objectives have been achieved. The original research questions of this thesis are answered. Limitations of this research are considered, and future research directions are recommended and their implications are suggested.

In Table 1.1 all the hypotheses of this thesis and the chapter that they have been addressed are summarised:

Table 1.1: Thesis hypotheses

Hypothesis	Chapter (s)
Our team formation models of temporary project teams can show how team formation affects resulting team performance..	3,4,5
There is a relationship between the *personality makeup* of a project team and its resulting team performance.	5, 9, 11
There is a relationship between personality and writing style	8
The team composition can be predicted by using some personality-related factors	7,10

In Table 1.2 the main research question and the results of each chapter are summarized.

Table 2.2: The Summary and flow of the 12 chapters of the thesis

Chapter Title	Research Questions	Achievements
Chapter1: Introduction	What is this thesis about?	An overview of the flow of the thesis is presented.
Chapter 2: Literature Review	What are the relevant concepts used in this thesis, and what are their shortcomings?	The literature about the main concepts that are used throughout the thesis is reviewed and their limitations and our contributions are highlighted.
Chapter 3: Evaluating the Effect of Team Formation on Team Modelling	Can team formation mechanisms affect the performance of software development teams?	The role of the team formation mechanism in the performance of software development projects is investigated, and it is concluded that team performance depends on the way that a manager assigns staff to a team.
Chapter 4: Team Formation Model in	Can team formation mechanisms affect the performance of self-assembly collaborative learning	This chapter demonstrates that the way that people form into a team indicates their improvement in knowledge and skill and also

Collaborative Learning	teams?	their team performance.
Chapter 5: Team Formation Model and Game Environment	Does the personality of team members in a self-assembly game environment affect the teams' composition and performance?	An agent-based model shows how the personalities of agents play a role in the composition and performance of their teams in a game environment.
Chapter 6: Discussion on The Role of Team Formation in Team Modelling	How useful would be a Decision Support model that covers the team formation mechanism?	In Chapters 3, 4, and 5, we presented three models that demonstrate the role that including team formation mechanisms can play in team performance, and in this chapter we discussed how these models can be used in a decision support framework for researchers, managers and website designers.
Chapter 7: Modelling the Effects of Personality on Team Formation	How can we model team formation in self-assembly teams and what is the role of personality?	A model is presented that describes the process of team formation and the role of personality in this process.
Chapter 8: Dataset for Self-Assembly Teams	How can real data be extracted to evaluate the model presented in Chapter 7?	Real data about the composition of temporary teams were gathered from Python project developers, but because their personalities were not directly available, another contribution was added in this chapter: a model that infers personality from text usage.
Chapter 9: Exploring the Role of Heterogeneity in Performance of Teams	Does heterogeneity improve the efficiency of teams as is claimed in some of the published literature?	Using a Bayesian model and the data that were gathered and discussed in Chapter 8, it is shown that there is a positive relationship between team heterogeneity and their performance. This is one of our assumptions used in Chapter 10.
Chapter 10:	To what extent do the hypotheses	Using the data gathered in Chapter 8 and the

Demonstrating the Usability of the Team Formation Model	in Chapter 7 have an effect on team formation?	positive relationship between team heterogeneity and their performance, we showed that four factors (out of 6 factors) presented in Chapter 7 have an effect on team formation. And the agent-based modelling shown has significant potential for prediction of future team composition.
Chapter 11: The Relationship Between Personality and Team Performance	What is the approach that should be chosen in organisations for discovering the relationship between team personality and performance?	This chapter has mainly a methodological contribution and suggests a data-driven approach for finding the relationship between team personality and performance. Moreover, we extract some rules about the relationship between team personality and performance by using the data gathered and discussed in Chapter 8.
Chapter 12: Conclusion and Discussion	What are the results of this thesis?	This chapter returns to the problem statement of the thesis and how the research objectives have been addressed through the thesis.

CHAPTER 2

2 LITERATURE REVIEW

In this chapter, the literature about the main concepts of this thesis and their limitations are discussed. The first part of the literature study concerns the behaviour of teams (such as their performance and ad-hoc team assembly) and the effect of personality on team behaviour. Because the components of the self-assembly teams have a degree of agency, it is concluded from this part of the literature that using the agent-based modelling paradigm is promising for meeting our objectives. Therefore, the second part discusses what agent-based modelling is and how it can be applied in the modelling of teams. In order to validate our model that is presented in Chapter **7**, it is necessary to relate personality to linguistic style. So, the third part of this chapter reviews the literature about this relationship.

This chapter is organised as follows. An overview of the field of self-assembly teams is provided in Section 2.1. A background on the concept of personality is provided in Section 2.2. The relationship between personality and team performance is explained in Section 2.3. In this section, a deeper analysis is provided for team performance in software projects. An introduction to agent-based modelling and in particular the application of agent-based modelling in team behaviour and personality is provided in section 2.4. An overview of the relationship between personality and writing style is provided in section 2.5. The following table shows how different concepts are used in the rest of the thesis.

Table 2.1: The usage of concepts in different chapters of this thesis

Concept	Personality	Self-assembly teams	Agent-based modelling	Team performance	Linguistic style
Chapter 3	■		■	■	
Chapter 4	■	■	■	■	
Chapter 5	■	■	■	■	
Chapter 6		■	■	■	
Chapter 7	■	■	■	■	
Chapter 8	■				■
Chapter 9	■	■		■	
Chapter 10	■	■	■	■	
Chapter 11	■			■	
Chapter 12	■	■	■	■	■

2.1 Self-Assembly Teams

Traditionally, the subject of the optimal composition for performance of teams has been an area of interest for researchers (Zaccaro & DiRosa, 2012). *Team composition* describes how the combination of individual characteristics improves team's performance. Nieva, Fleishman, & Reick (1985) found that *team size* has an effect on management and performance of a team, whereas other studies have found team size to be unrelated to performance (Martz, Vogel, & Nunamaker, 1992). Individuals' *skills* are critical for team performance and the positive correlation between team skill composition and performance is shown in many studies (e. g. Brannick, et al. 1997). Some other studies investigated the role of the *heterogeneity of some traits* among team members. Stewart (2006) found that heterogeneity is more beneficial for doing a creative task, and less beneficial for management teams who coordinate and direct other teams in the organization

Task design is another important factor that is crucial in analysing team behaviour. Task design refers to how activities to be performed by teams are integrated and differentiated (Stewart, 2006). *Task interdependency* is the most important of the parameters in task design which are studied in the literature (Pagell & LePine, 2002). Task interdependence refers to the extent to which a task requires an exchange of information and resources, and the extent to which the outcome of one task affects another task (Andres, 2015).

In addition to team composition and task design, *team structure*, which refers to the nature of the relationship among team members, is also important (Wong & Burton, 2000). Some factors such as *physical dispersion* (Wong & Burton, 2000), *centralization* (Kim & Burton, 2002) and *formalization* (Andres, 2015) affect the team structure. In the majority of studies on teams, the role of leadership is examined as the link between the team and the organization (Stewart, 2006). Some studies have shown that autonomy of teams improves team performance, especially when a high degree of innovation is desirable (Stewart, 2006).

Traditionally, researchers and managers have analysed how the composition of teams based on the members' individual differences, such as knowledge, skills, and personality, can create more effective groups of workers (Stewart, 2006). Modern teams tend to be self-assembling, which adds another dimension of complexity to the study of teams. Teams are sometimes identified as being of four main types: 1) work teams that are responsible for units of work and their membership is stable and well-defined, 2) management teams that are coordinated and direct other teams in the organization structure, 3) parallel teams that are permanent teams that pull together some people from different disciplines and exist in parallel with the formal organization of structure, and 4) project teams which are limited-time teams (Cohen, 1997).

In the first three of those team types, individuals are staffed into teams. In contrast to manager-appointed teams, project teams are often self-assembled teams with independence over the process of team formation.

A great majority of teams are classified as project teams and since they are often ad-hoc groups of distributed collaborators, also called ad-hoc teams. Project teams are time limited and produce a one-time output (Cohen, 1997). Unlike the other types of teams, project teams often do not have well-defined boundaries or stable membership, and when a project is completed; team members re-engineer and restructure the team for the next project. In these teams, individuals usually have freedom to make decisions about their membership, commitment, and workloads within the teams. Self-assembly of teams happens in a wide variety of organizational contexts. Some examples include crowdsourcing platforms, scientific collaboration teams, open-source software development teams, online games and so on. Before the recent IT evolution, the historical examples of these ad-hoc teams were common in the construction industry, Hollywood and other film industries, and voluntary tasks in the global and local crisis area, such as earthquake and tsunami response teams. As an example, when earthquakes happen, volunteers join one of the various teams that are self-assembled to help the citizens (e.g. food and water distribution teams, medical supply provision team, and helping rescue efforts).

Project teams are becoming dominant because they are facilitated by the online environment, where there is awareness of the necessity and significance of these teams. For instance, cross university collaboration between researchers has been sharply increasing since the mid-1970s (Wuchty et al. 2007). The "Communication Revolution" has given birth to the phenomenon called the "death of distance" (Sempsey, 1998).

By definition, self-assembling teams have a degree of agency (i.e. autonomy) over the team formation process. However, these teams vary with regards to this assembly autonomy, ranging in agency from limited freedom to highly autonomous, with no formal leaders.

In spite of the rapid uptake of self-assembly teams in IT environments (e.g. open source software development and the numerous software contractors (individuals) working on various proprietary projects across the globe), there is little common understanding or agreement about how these teams are assembled (Contractor 2013). The team assembly mechanism in the literature is viewed either as a design process undertaken by managers, or as a self-organizing process (Wax, 2015).

Previous studies have tried to analyse the mechanisms behind forming a group. The study in this thesis is different inasmuch as it uses agent-based modelling, whereby the social dynamics of the groups are derived from their members' personalities. The social dynamics are related to some personality dimensions associated with how people interact with each other. For example, extroversion might improve cohesion among a team over time (Ball, G., et al. (2000). Using the social dynamics, we can predict future team composition and team performance. There appear to be no studies of a similar nature to this study in the relevant literature.

In order to understand the mechanism governing the composition of social groups, Ruef et al. (2003) conducted a survey that analysed a data set of 816 organizational founding teams from the U.S. population sample. They concluded that *homophily* and *network constraints* based on strong ties have the most significant influence on group composition. Homophily refers to selection of team members based on similar characteristics such as gender, ethnicity, appearance, nationality, and so on. In addition to homophily, selection of the other team members are limited because of having strong or weak ties with the other people in the network.

Roberts et al. (2006) analysed data from 288 contributors to the Apache Software project and found that the developers' motivations for joining a team were impacted by both *intrinsic motivations* such as their past performance, and *extrinsic motivations* such as being paid.

Hahn et al. (2008) by studying 2,349 open-source software (OSS) development teams on SourceForge.net, suggested that *prior relationships* which had been developed in past collaborations motivated contributors to join a project team. In addition to empirical studies, some studies investigated the team assembly mechanism by using computer simulation. Guimera et al. (2005) proposed a model for the self-assembly of teams based on three parameters: team size, the proportion of newcomers, and the tendency of incumbents to repeat previous collaborations, and they concluded that the team assembly mechanism not only determines the structure of the collaboration network but also the team performance.

A team model developed by Johnson et al. (2009) showed that the *average tolerance level in deciding to leave a group after comparing how close his attribution is with the other group members,* and the *attribute range for each population (*homophilic kinship) affected the individuals' decisions regarding team formation. They validated their model with real data from street gangs and demonstrated the ability of their model to predict the context specific domains.

Various researchers have suggested that previous *collaboration experience* is one of the main factors that determine the self-assembly mechanism (Guimerà et al., 2005, Cummings & Kiesler, 2008, Hahn et al., 2008, Roberts et al., 2006, Ruef et al., 2003). In addition to the previous experience individuals have had with the performance of past groups, *interpersonal attraction,* which is the attitudinal positivity one person has toward another person and which motivates human beings to connect with others, is another factor. The literature has explored a variety of ways that people are attracted to one another. Some examples include, age, race, sexual orientation, personality, attitudes, and beliefs (Wax, 2015).

Group composition and the various other factors that affect the assembly and the performance of groups must be included in any model that tries to model coalition formation. One of these factors is the personality of team members, and any decision in selecting a team member is highly connected with the personality, a consideration that is not fully covered in the similar studies.

2.2 Personality

Recent works on personality have significantly shaped the understanding of our world. The company behind USA President Donald Trump's online campaign was the same company that had worked for the British "Brexit" campaign, called Cambridge Analytica (cambridgeanalytica.org). It focused on measuring psychological traits such as personality to customize the messages in online networks, and it has been argued that they successfully changed the opinions of numerous people in the "Trump", "Cruz" and "Brexit" political campaigns. This points towards the significant role that analysing personalities plays in modern life.

Teamwork is one area where the importance of personality is emphasized as a factor in predicting people's behaviour. Despite the importance of personality in team work settings, it has not been given equal coverage (as a factor influencing teamwork similar to other factors) in the academic literature (LePine et al., 2011).

To pursue the examination of individuals' behaviour in teams, a reliable characterization of human personality is needed. There are various psychological classifications of personality types. A System of Needs was developed by Murray (1938). He believed that some needs are inherent in our psychological nature, such as achievement, dominance, affiliation, nurturing and so on. His theory describes personality in terms of need, where stronger needs are expressed more often and as a result produce intense behaviour.

Eysenck (1950) believed that all people can be described as having one of two super traits: Extraversion or Stability. By using factor analysis he reduced behaviour to a number of factors which can be grouped together under separate headings, called dimensions. His work was influential for several personality models such as 16 PF (Cattell et al. 1988).16PF explains the variations in human personality by a model that has sixteen personality traits and uses a statistical procedure known as factor analysis.

Using Jung's Personality Theory (Jung, 1921), Briggs and Myers (1962) developed the Myers-Briggs Type Indicator (MBTI) which indicates the preference of people for gathering information, making decisions, dealing with the outer world and focusing their attention.

The Five Factor Model (FFM) (Costa & McCrae, 1992) describes the human personality as having five broad factors, such as Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism, and these factors are summarized as follows:

- **Openness:** They appreciate new experiences, art and creativity and they are more likely to hold unconventional beliefs.
- **Conscientiousness:** It shows discipline and dutifulness, and this group of people have a preference over planned behaviour rather than being spontaneous.
- **Extraversion:** They enjoy being engaged with the outer world and interacting with people.
- **Agreeableness:** They value getting along with others, and they have an optimistic view to human nature.
- **Neuroticism:** They have a tendency to experience negative emotions such as depression and anger.

MBTI and FFM are widely used as personality models these days (Capretz et al., 2015). It is the researcher's opinion that gathering data about FFM is neither easy nor reliable (Boyle et al. 2008). We used MBTI over FFM for mainly two reasons. First, FFM does not introduce a standardized cluster to compare groups of people, and rather than grouping people into a personality group it determines the score in all five categories. However, by using MBTI, people perceive themselves as fitting into a personality category, and this sense of belonging to a group makes them more social and willing to express their personalities in public. Second, FFM measures only what appear to be the positive "qualities" of personality. For example, a high score in Openness is regarded as positive, and low score is regarded as negative. Whereas, in MBTI, neither Sensing nor iNtution are regarded potentially as positive or negative characteristics. This issue might tempt people to fake their personalities (Martin 2002). People who do not want to be judged are more likely to self-identify with their personality as measured by MBTI types.

In this study, it was observed that people in social networking websites found the MBTI test to be useful as a way of understanding themselves and how they differ from each other. They appeared to prefer to express their uniqueness using the MBTI dimensions. Perhaps this is the main reason that, despite claimed shortcomings that this personality model is not developed based on a rigorously scientific approach (Boyle, 1995), MBTI has persisted as one of the most popular tools for companies and career counsellors in many domains, including the domain of software engineering. According to Capretz et al., (2015), in software developer personality research, MBTI is the most popular test and is used in 48% of the studies, while 9% of those studies use Keirsey's Temperament. So, according to that report, 57% of the reviewed studies used tests based on Jung's Personality Type Theory, while the Five Factor Model was used in only 19% of the studies. We note also that Choi et al. (2009) indicated that MBTI is an excellent choice for team formation studies and that FFM is used less in this domain.

In response to the concerns expressed about the FFM model earlier, and the support for MBTI in the research literature (as discussed above) and its adoption in companies, this study employs the MBTI scheme. In the following section the MBTI model is explained.

Moreover, MBTI has been widely used in the modelling of personality in multi-agent systems. Campos et al. (2009). by integrating MBTI personality into the reasoning process of BDI agents, demonstrated that different MBTI personalities result in variations in the decision making process. Salvit and Sklar (2011) integrated MBTI into a sense-plan-act structure and demonstrated that different MBTI personality types lead to quite different outcomes. Moreover, Du, H., & Huhns, M. N. (2013) set up some experiments, and they showed that humans with different MBTI personalities treat other humans and agents differently.

2.2.1 MBTI

The MBTI is based on the work of Jung (1921). However, it also has similarities with Hippocrates' views from some twenty-five centuries earlier. Hippocrates spoke of the four gods Apollonius, Dionysus, Epimetheus, and Prometheus. In other words, he suggested that people can be categorized into four personality profiles, sanguine (optimistic and social), choleric (short-tempered), melancholic (analytical and quiet), and phlegmatic (relaxed and peaceful).

Inspired by Hippocrates' four temperaments (Sudhoff, 1926), the MBTI has been developed today into a standard system that is used in the consulting business and academia. The MBTI is based on a psychological type scheme and has four personality dimensions in which the names representing extreme ends of each dimension:

- **Extraversion** vs. **Introversion (E-I)** – the degree to which one faces the outer social world or keeps more to one’s self.
- **iNtuition** vs **Sensing (N-S)** – the degree to which one gathers information that is in concrete, objective form, or information which is more abstract and understood according to one’s inner compass.
- **Thinking** vs. **Feeling (T-F)** – the degree to which one is more empathic and attempts to see things from given perspectives, or makes decisions based on logic and demonstrable rationality.
- **Judging** vs. **Perceiving (J-P)** – the degree to which one wants things settled and organized, or flexible and spontaneous.

These four dimensions are categorized and explained in Table 2.2.

Table 2.2: Four dimensions of personality as measured by MBTI

	Extraversion (E)	**Introversion (I)**
Where people focus their attentions	Prefer to focus on the outer world	Prefer to focus on the inter world

The way people gather information	**Sensing (S)**	**iNtution (N)**
	Prefer to focus on present and concrete information	Prefer to focus on the future, patterns and possibilities
The way people make decisions	**Thinking (T)**	**Feeling (F)**
	Prefer to make decisions based on logic and demonstrable rationality	Prefer to primarily make decisions based on values and concerns of other people
How people deal with the outer world	**Judging (J)**	**Perceiving (P)**
	Prefer to be settled and organized	Prefer to be flexible and spontaneous

Thus the 16 types are typically referred to by an abbreviation of four letters—the initial letters of each of their four type preferences. For instance: ISFJ stands for Introversion (I), Sensing (S), Feeling (F), and Judging (J).

In association with the MBTI type, David Keirsey developed the Theory of Temperament (1988). He combined MBTI types into four sets of preferences which are Knowledge Seekers, Duty Seekers, Action Seekers and Ideal Seekers. These are explained in more detail in Chapter 3.

2.3 Personality and Team Performance

Relating personality to group effectiveness as a significant subject of research has a long history (Mann, 1959). In order to measure the personality of individuals throughout this thesis, a scale of 0 to 100 is employed and explained as follows:

- E-I (Extraversion/Introversion): >=0 and <=50→ Extraverted; >50 and <=100 →Introverted.
- N-S (iNtuitive/Sensing): >=0 and <=50→ Intuitive; >50 and <=100 →Sensing.
- T-F (Thinking/Feeling) : >=0 and <=50→ Thinking; >50 and <=100 → Feeling.

- J-P (Judging/ Perceiving): >=0 and <=50→ Judging; >50 and <=100 →Perceiving.

To model the team performance aspect and measure the collective team attributes, two additional indicators proposed by Neuman, Wagner, & Christiansen (1999) 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.

Teams that are high in terms of TPD are described as heterogeneous, whereas teams that are low in terms of TPD are referred to as homogeneous.

Tziner (1985) introduced two theories of social psychology that explain how team composition affects team performance:

- Similarity Theory predicts that homogeneous teams are more productive because of the mutual attraction shared by their members.
- Equity Theory predicts that team performance is higher in heterogeneous groups.

Muchinsky and Monahan (1987) proposed that there are two types of person-environment congruence: supplementary and complementary. By supplementary, they mean the degree to which a person fits into an environmental context because she or he supplements characteristics of, or has some similar characteristics to, other people in this environment. Complementary means the degree to which a person fits into an environment because she or he serves to complement the features of that environment. This categorization may help to explain whether heterogeneous (high Team Personality Diversity (TPD)) or homogeneous (low TPD) teams will result in better job performance.

Research findings regarding the relationship between TPD and group effectiveness are mixed (Bowers et al. 2000). Some researchers suggest that low TPD results in more effective performance (e.g. (Day & Bedeian, 1995)), while other researchers suggest that high TPD results in more efficient performance (e.g. (Aamodt and Kimbrough 1982)), while still other researchers suggest that high TPD on specific traits results in effective performance (Barry & Stewart, 1997b).

Both of these competing hypotheses predict performance based on team composition, but their predictions lead to different conclusions. Weirsema and Bantel (1992) have noted that homogeneity in teams brings about a shared language among team members and improves integration and communication frequency. As a result, they suggested that homogeneous teams would be more likely to perform better on the tasks that require high levels of co-ordination. In contrast, Bantel (1994) predicted that homogeneous teams would perform poorly because of a lack of openness to new sources of information. However, it is argued that any study about the relationship between personality of team composition and team performance is incomplete if we ignore the nature of the task (Stewart et al. 2006)

Team Personality Elevation (TPE) is another important factor that determines the functions and performance of groups. For example, McGrath (1986) showed that high TPE Conscientiousness and Openness are important factors in research teams (McGrath, 1986).

In general, the type of tasks can be critical for understanding the relationship between composition and performance. Some tasks require a high level of cognition and complexity, while some other tasks require a high degree of co-ordination and teamwork. The link between personality, team performance and task type is elaborated in Chapter 3.

2.3.1 Team Performance in Software Projects

In the literature on the software development domain, several investigations have reported that personality is a key factor in determining success or failure (André et al. 2011). Some investigated the effects of similarity or dissimilarity among team members on performance (Bradley & Hebert, 1997). However, results reported in this domain showed conflicting evidence about the relationship between personality and team success. Some studies showed that personality diversity in teams is not related to team effectiveness, such as Miller & Yin (2004) and Peslak (2006). In contrast, some other studies showed that diversity is important in terms of personality (Pieterse et al., 2006, Rutherfoord, 2001 and Lewis & Smith, 2008). Moreover, some studies found evidence about the relationship of one particular dimension on overall team performance. For instance, Karn & Cowling (2006) showed that teams which had predominantly introverted (I) individuals were less effective because of communication problems. Choi et al. (2008) found that diverse Sensing and iNtuition preferences between members would encourage them to challenge each other and offer a wider array of solutions. Also, they considered different compositions of pair programmers. In their studies, the most successful teams were diverse teams who were not totally opposite (e.g. TN (Thinking and iNtution) –FS (Feeling and Sensing)) or alike (e.g. TS-TS). One of the successful pairs was ST-NT, and based on that categorisation they concluded that the similarities with the Thinking-Feeling dimension provided common ground for reconciling differences and that the diversity in the iNtuition-Sensing dimension helped them to generate new ideas. In their study, teams with dissimilar personalities were found to be more successful than alike teams.

Self-organizing teams have taken centre stage in software engineering (Hoda et al., 2013) and although some attempts have been made to explore how these agent teams in software development domain self-organize (e.g. Hoda et al., 2012), these studies are not sufficient and there is little understanding about the assembly of these teams (Hoda et al., 2013).

2.4 Agent-Based Modelling

Simulation systems have been used in several domains such as air traffic and weather since the 1950s (Luke 2015). A particular simulation technique that has widely been used in recent years is known as Agent-Based Simulation (ABS). An agent is defined as a software entity which has four main characteristics: it is autonomous, reactive, pro-active, and capable of social interaction (Wooldridge 2009). The ability of individual agents to make decisions is a key factor that distinguishes agent-based models from other models. Agent-based modelling has become increasingly popular in the social sciences, since it offers the possibility of building "what-if" scenarios and it allows a modeller to represent individual autonomous entities and their social interactions. Agent-based modelling is widely used in different disciplines such as biology and social science (Wooldridge 2009). For instance, one might conduct some experiments to analyse why certain behaviour evolves over time and what would be the effect of different circumstances on this behaviour. Computer simulations of these agent-based models enable researchers and practitioners to gain additional insight into a complex system's behaviour. Social simulation is a research field in which computers support human reasoning activities to study issues in the social sciences (Carley, 2002). Agent-Based Social Simulation (ABSS) is a combination of social science and multi-agent simulation. Using these models, we can learn about the reactions of the artificial agents and translate them into the results of non-artificial environments. The main objectives of ABSS are a) understanding basic aspects of social phenomena, b) prediction, and c) research, testing and formulation of hypothesis (Gilbert, N., & Troitzsch, K. (2005)). Some examples about these simulations are provided in Sections 2.4.1 and 2.4.2.

In the process of agent-based modelling, a bottom-up approach is used to model the components of a system. As a result, the structure of the system is not predefined and can be tested in a simulation environment. Also, agent-based modelling is a powerful tool that enables us to monitor the emergence of system behaviour and responses.

2.4.1 Agent-Based Modelling and Team Behaviour

Many cognitive studies deal with the emulation of different mental processes such as decision-making, planning and learning to reproduce human behaviour. There are several architectures that model different mental processes. For instance, SOAR (Laird, 1987) is a cognitive architecture that represents knowledge, learning mechanisms, and long-term memories. Another example is ACT-R, which represents human knowledge in two categories: declarative knowledge and procedural knowledge (Anderson et al.,2004). Some other examples include CLARION (Keijzer, 2003), EPIC (Kieras & Meyer, 1997), 4CAPS (Just & Varma, 2007), and CHREST that are integrative architecture, consisting of a number of distinct subsystems that has been used to simulate several tasks in cognitive psychology and social psychology (Gobet & Lane, 2010). A complementary approach to these cognitive models is using agents which are autonomous entities and have the ability to interact with other agents and with the environment.

According to Castelfranchi & Rosis (1998), the concept of personality has been introduced into socially autonomous agents for various reasons. Mainly it is used to model natural societies of people with different personalities. Also, personality is widely used to construct different strategies in multi-agent systems (Sichman et al, 1998). Personality affects how agents react, and different distributions of personality in a society or organization can develop different attitudes and behaviour (Bowers et al. 2000).

Agent-based modelling is suitable for dealing with systems that have the following conditions (Dam & Nikolic, 2006):

- The system has a distributed character.
- The environment is highly dynamic.

- The interactions in the system are flexible.
- The subsystems are reactive, pro-active, cooperative and have social ability.

In the social sciences, the importance of groups as a subject of study is widely investigated and recognized as a structure that cannot be easily characterized (Geard & Bullock, 2008). Because of the autonomous nature of groups, agent-based modelling seems to be a suitable approach for predicting and explaining the complex systems in social sciences.

An autonomous agent may not be capable of independently fulfilling its own individual goals due to various reasons such as lack of knowledge and skills and they often might form a coalition. Therefore agents may engage in coalition formation to assist each other and achieve their individual goals. Unlike self–assembly teams, coalition formation has been viewed as a general principal in social systems and has received much attention (e.g. Ketchpel, 1994). Most researchers have focused on agent coalitions from two perspectives: Game Theory (e.g. Shehory & Kraus, 1998) and social reasoning (e.g. Sichman et al., 1998).

An agent coalition consists of a number of co-operative agents who work toward a common performance goal (Fan & Yen, 2004) and in this sense, the concepts of coalition can be used by self-organising agents. Individual members attempt to maximize the utility of them, whereas coalition teams try to maximize the utility of the team. Agent-based modelling is widely used in teamwork modelling, since it enables the integration of various dimensions of team behaviour such as communication, co-ordination, collaborative learning, cross monitoring, and so on (Fan & Yen, 2004). Some examples of these studies include models for analysing the effects of specific individual, social, and contextual characteristics on team performance (Martinez-Miranda 2011). We now discuss some of the key models developed by researchers.

Claudia Pahl-Wostl et.al (2004) developed a model for analysing the behaviour of a group of agents managing a common pool resource. In this model, agents were characterized by a set of attributes such as the level of co-operation, fairness, conformity, commitment and trustworthiness, and it is shown how different characteristics produce different responses to social interactions.

Wu and Hu et al. (2008) proposed a multi-agent simulation approach that analyses the group's behaviour in the adaptation of a new e-government application. This model characterizes individuals through attributes such as the level of accepting information technology, existent power of groups, the degree of obtaining interest, and the value types of the agents. Marreiros et al. (2005) presented a model for the formation of decision-making groups in which each agent has three parameters: area of expertise, interest topics, and availability. Later on Novais et al. (2006) extended this model by including a set of emotions for agents. Dong et al. (2008) developed a model that shows how team effectiveness emerges from the relationships among members. Breso & Pérez (2013) developed a model that analyses the influence of a set of personal characteristics and contextual factors on creativity at both the individual and the group level.

Rojas et al. (2011) developed an agent-based model to determine the combination of team composition, organizational characteristics and co-ordinating methods that result in the best performance. Martinez-Miranda & Pavon, (2011) developed an agent-based simulation model to support the formation and configuration of work teams. This model represents and analyses the performance of the team as a consequence of four human attributes: personality type, emotional state, social-related skills and cognitive abilities.

The agent selection for teams depends on the agents' capabilities, tasks' requirements and allocation process itself and discovering suitable agents for a task may include ranking techniques such as the bidding process (Tidhar et al., 1996). Tambe et al. (1999) developed STEAM which is an architecture for representing and adopting team behaviour that defines how agents should reason over joint commitment, shared goals and joint plans.

Theories of Joint Interactions (Cohen & Levesque, 1991) and theories of Shared Plans (Grosz & Sidner, 1988) are popular for building multi-agent teamwork frameworks. The STEAM (Tambe et al., 1999) a teamwork model borrows strength from both theories. Computational Organizational Performance (CORP) (Carley & Lin, 1997) is another framework that models organizations by taking into account the organizational processes, individual experiences, and the environments of the task. CORP simulates a diverse set of decision making problems in and between organizations.

In all the examples above, there is no clear relationship between cognitive-related capabilities, particularly personality, and social-related capabilities and their team formation behaviour. This thesis presents an agent-based model to support the decision-making process for self-assemby teams. We specifically focus on the agent's *personalities* and their influence on the self-assembling process.

2.4.2 Personality and Simulation

Doce et al., (2010) identified four behavioural processes in the agents which are strongly influenced by personality: emotions, planning, coping behaviour and expressivity. The personality traits describe the feelings that agents experience in connection with certain emotions (Arnold, 1960). Personality influences several aspects of human beings which are involved in their planning processes, including persistence and motivation (Pervin, 2003). Psychologists have shown that personality traits can describe an individual's coping behaviour (David & Suls, 1999). The diversity with which agents express their emotions is also related to their personality traits (Arnold, 1960).

In the studies in the area of human personality in connection with agent-based systems, the "traffic" concept is one of the popular research domains. For example, Lützenberger et al. (2014) developed a traffic simulation framework that includes a personality model for drivers. Crowd simulation is another area of interest that introduces different personalities into agents which influence the behaviour of crowds, for instance, their behaviour during fire evacuation in a theatre or stadium. Durupınar et al. (2008) proposed a mapping from personality traits to existing behaviour types and parameters in crowd behaviour and analysed the overall emergent crowd. Personality has been introduced into agents for other purposes, such as entertainment and creating life-like characters in the animated world (Loyall, 1997), human-machine interaction in interfaces and dialogue systems (Dryer, 1999), and so on. A recent example of life-like character in the animated world is Inside out movie (2015) which is the story of Riley, an 11-year-old girl, who is struggling with the unstable emotions of youth. In this movie, the viewers experience a conceptual version of Riley's mind through her personality and memories and how she processes the world through her thoughts and mood. This movie takes advantage of simulation and the recent studies about the relationship between personality and memory. For instance, studies show that Extraverted men in the Five Factor Model tend to remember more positive moments, while women who rate high in neuroticism tend to remember more negative moments.

As mentioned earlier, personality plays a crucial role in group scenarios, and it determines how individuals with different characters reason about other characters and groups.

Individual aspects of agents, such as their personalities, can help to predict and explain the behaviour of groups who are committed to a collaborative task. The interactions of these autonomous agents have been addressed by several researchers (Guye-Vuillème, 2004).

PsychSim (Marsella, 2004) is an agent-based modelling tool that allows end users to implement social scenarios concerning the dynamics of social influence. By parameterizing a diverse set of goals, relationships, private beliefs, and mental models for each entity, the end users can explore how individuals and groups interact and how these interactions can be influenced.

The self-assembly of teams and how they update their beliefs in response to their interaction with other agents and how their personality types affect their team selection is ignored in the previous works in the area of simulation and personality.

2.5 Personality and Text Analysis

People express themselves in their own unique style and their language expression differs from person to person. Forms of "linguistic fingerprinting" frequently have been used to distinguish letters written by soldiers in the 1800s (Broehl & McGee, 1981), to distinguish verbal styles of political leaders (Hart, 1984), to determine the authorship of otherwise anonymous books (Foster, 2014), and to distinguish the behaviour of mailing-list users (Rigby & Hassan, 2007), (Licorish & MacDonell, 2014b).

As a result, text-mining techniques can be employed to discover textual patterns in the various personality types. Text-mining is an extension of data mining to textual data, and attempts to extract meaningful information from textual data (Tan, 1999). Nowadays, virtual teams use text-based tools (e.g., wikis, mailing lists, blogs, and instant messengers). Extracting knowledge from these texts provides managers and researchers with opportunities to manage teams' behaviours. Previous researchers have shown the relationship between personality and linguistic styles (Pennebaker et al., 2001). People express themselves in their own unique styles. Similar to the spoken language, written language is different from person to person.

Pennebaker et al. (2001) developed Linguistic Inquiry and Word Count (LIWC) as a text analysis tool. LIWC is based on counting function words and uses a psychometrically-based dictionary to divide the different counts into meaningful dimensions. The program searches for more than 4,500 words and word stems and categorizes them into four categories: 1) linguistic processes (e.g., Personal Pronouns, Adverbs, and Prepositions), 2) psychological processes (e.g., Social Processes, Positive Emotion, Negative Emotion), 3) personal concerns (e.g., Work, Achievement, Leisure) and 4) spoken categories (e.g., Assent, Non-fluencies, Fillers).

Pennebaker & King (1999) investigated how people with different Five Factor Model (FFM) personality profiles (Costa & McCrae, 1992) have different writing styles. Their work is insightful, but because of some limitations in the participants and domains, they encourage further conformity investigations. They studied three different samples to examine how language is used in the texts to reflect personality styles. The first sample contained 15 residential patients in an addiction treatment centre who were asked to complete a "significant event sheet" at the end of each day about the most significant events of the day. Sample 2 contained 34 students who completed their class assignments. The third sample was published as an abstract by social psychologists. Their results suggest that the linguistic style of the writing samples is meaningful for exploring personality. However, they argue that language dimensions are weakly correlated with the FFM and have been greeted with scepticism, and further investigations are required (Pennebaker & King, 1999)

The opinion of this researcher, however, is that in the assignments and essays which were used as the main sample data in the study by Pennebaker & King (1999) people may not have expressed their real feelings, moral attitudes and values on that particular topic, and that if the writing were to focus on other topics, other characteristics and patterns might emerge. Behaviour is discriminative, rather than consistent, across situations and assignments, and scientific articles do not always cover a sufficient variety of situations. Also, assignments and scientific articles may mainly relate to verbal abilities rather than personalities.

In social networking websites, people are free from the constraints that a particular topic would otherwise place on them, since they voluntarily choose the discussion topics and unlike assignments they focus on their opinions, rather than on showing their intelligence and verbal ability. In addition, social networking websites are rich in text types, since they enable users to create different text content in the forms of posts, social media, comments and blogs. As a result, this thesis argues that the texts from social networking websites can be the most suitable platforms to reveal the relationship between these texts and the personalities of their writers.

The correlation between users' behaviour in social networking websites and their personalities has been the focus of several studies in recent years. Personality traits of RenRen users (www.renren.com) have been analysed, since it is one of the most popular social networking websites (Bai et al., 2012), as are the traits of users of Facebook profiles (Golbeck et al., 2011) and Twitter (Qiu et al., 2012). However, efforts in this area mostly focus on the development of recommender systems for selling services, and do not provide a model to predict the personality from the text usage.

In summary, in order to address the limitations of the previous studies that tried to find an association between language use and personality, Chapter 6 will develop and report on novel correlations between linguistic style and personality. These limitations are listed as follows:

1. To the best of our knowledge, there has been no study which focuses on the relationship between LIWC dimensions and MBTI. However, (Lee et al., 2007) introduce correlations between the Korean version of Linguistic Inquiry and Word Count (KLIWC) and Myers-Briggs analyses.
2. Previous studies collected texts under laboratory settings. As discussed earlier, people may not express their real feelings, moral attitudes and values when they did not choose the topic they are asked to write about.
3. In the previous studies the size of samples has not been considerable, and each writing sample was less than a few thousand words. Moreover, these data are gathered from a small number of participants, which limits the results.

2.6 Conclusion

This chapter has provided an overview of previous works on teamwork modelling and self-assembly teams. It has also provided coverage on the works on personality analysis and how personality is used in understanding teams' behaviour and agent-based modelling. Moreover, the relationship between linguistic style and personality was studied. The concepts described in this chapter will be used throughout this thesis. The next chapter demonstrates the importance of adding the team formation mechanism as another level of complexity for studying team behaviour.

CHAPTER 3

3 EVALUATING THE EFFECT OF TEAM FORMATION ON TEAM PERFORMANCE

In the previous chapter, we argued that the success (or failure) of software development groups highly depends on the group members' personalities, as well as their skills in performing various tasks associated with the project. Traditionally, managers select an optimal team composition by considering factors such as skill, knowledge and abilities of employees. Although considering these factors are important, one additional level of complexity needs to be added in the modeling team. This level, which is a focus of this thesis, is *understanding the mechanism behind the formation of self-assembly teams*. Thus, in this chapter, we argue that the team formation mechanism is a key factor that influences team performance and understanding this mechanism is a vital factor for understanding teams.

Contemporary teams are frequently ad hoc groups and self-assembled. However, they vary in the degree of assembly autonomy. Understanding the mechanism behind the self-assembly teams is often neglected. In this chapter, we argue why this understanding is important and demonstrate how team performance can be affected by the team formation mechanism.

Moreover, this chapter explores the use of the Myers-Briggs Type Indicator (MBTI) as the basis for defining the personality of an agent. Modelling the behavior of teams is important in various domains such as psychology and software development. We focus on capturing personality as the main factor that governs human behavior in a team. In this chapter, we demonstrate the usage of MBTI by implementing agents with different personalities.

We developed three computational models in three different environments: *software development*, *collaborative learning* and *gameplay* that are explained in Chapter 3, Chapter 4 and Chapter 5. In these models, by employing agent-based modeling, we investigate the role of team formation mechanism and its effect on the team performance.

In this chapter, we develop a computational model to evaluate the performance of software project teams based on *skill competency* in conjunction with *personality composition of* *teams*. To demonstrate the application of the model, simulation studies are then presented. The simulation outputs compare two team formation mechanisms in different tasks with different levels of changes in their requirements (i.e. changes in the complexity of tasks). In the experiments, we argue that the mechanism that managers select for staff allocation to a team is a key factor for team performance. The results from this model are published in Farhangian et al. (2015a).

3.1 Staff Allocation in Software Development Industry

This selection of employees to configure a team is known as one of the most important aspects of team effectiveness (Stewart, 2006), researchers have explored various factors that determine the fitness of a person into a team (Malinowski et al., 2008). In the software project teams, researchers mainly have discussed the personality as one of the most important factors which explain the relationship between team configuration and team performance (André et al., 2011) (LePine et al., 2011).

Having a formal model which is built into a decision support system that supports the assignment of human resource in the software projects has been an area of interest for several decades. Ngo-The and Ruhe (2007) developed a computationally efficient technique to assign human resources for solving problems in the software engineering domain. Otero et al. (2009) presented a methodology to assign resources to tasks by taking into account priorities of required skills for the task, required levels of expertise, and the existing capabilities of candidates.

The previous studies have produced inconsistent results in terms of the relationship between personality and software project team performance mainly because of two main constraints. Firstly, they mostly consider the individual aspects of employees without fully covering group factors such as cohesion, conflict, team structure and coordination. Secondly, they have not considered the dynamic nature of the task and the effect of team formation strategies on the performance of these tasks. In reality, various aspects of task dynamics such as changes in the task requirements affect the team effectiveness. As a result, any model for assigning human resources to teams is incomplete, unless it takes the team formation mechanism into account.

In order to address these limitations, in the first model of this chapter, by reviewing and applying relevant literature, a model is developed to calculate team performance based on personality and skills competency of team members. Then by using agent-based modeling, the role of the team formation mechanism in team performance is demonstrated. In this connection, we examine the relationship between the dynamic nature of tasks and managers' strategies for team formation by using computer simulation. We model the evolution of task performance in terms of two types of parameters: *task requirements* and the *personality distribution of employees*. The simulation results can support managers' decision-making with respect to task allocation.

In summary, we develop a comprehensive model by covering the findings with respect to the Belbin Team Roles and MBTI. Then we demonstrate that understanding the mechanism behind team formation is vital for understanding team performance in software projects.

3.1.1 Team Roles

As we discussed earlier, a team is not merely a set of individuals with some skills: they all bring their personality-related attributes to the team and these attributes can be dynamic and can be influenced by context and the behavior of others. One of the popular and influential theories that promote the understanding of managers and their effects on the team behavior is Meredith Belbin's theory (1981) of team roles. Belbin (2011) introduced a theory about the roles of individuals in teams. In each team, every member has a role that might affect the performance of the team. In an early publication, eight team roles were identified: Chairman, Shaper, Plant, Monitor-Evaluator, Company Worker, Resource Investigator, Team Worker, and Completer-Finisher. Later he added a ninth role, Specialist and renamed the Chairman to Coordinator and the Company Worker to Implementer (Belbin, 2012). Other researchers then raised the possibility that the relationships could be found between the roles and the MBTI types (Stevens, 1998). These roles are explained in Table 3.1 (Belbin, 2012).

Table 3.1: Belbin Roles

Team Role	Contribution	Allowable weakness
Plant	Creative	Ignores incidentals
Resource Investigator	Outgoing, Enthusiastic	Over-optimistic
Coordinator	Mature, Confidant	Manipulative
Shaper	Challenging, Dynamic	Prone to provocation
Monitor Evaluator	Sober, Strategic	Lacks drive to inspire others
Team Worker	Cooperative	Indecisive in crunch situations
Implementer	Practical	Somewhat inflexible
Completer	Painstaking	Inclined to worry unduly
Specialist	Single-minded	Contributes only on a narrow front

3.1.2 Relationship between MBTI and Belbin

Personality profiles and Belbin Team Roles (BTRs) suggest that personality and role tendencies are not independent (Stevens, 1998). Stevens and Henry (1999) tried to map these two instruments and they noticed that there is a different distribution of both BTRs and MBTI and from this distribution the personality related to the team roles could be determined, and Schoenhoff (2001) continued this **work and validated some of the previous findings.**

Myers also introduced a theory, namely MTR-i (Myers, 2002), which incorporates the idea of team roles, and **she** claimed people with different personalities are likely to have specifically correlated roles in a team. Table 3.2 compares the results of different studies (where X means no relationship between personality and Belbin role is found). For instance, in Henley report shown in Column 2 of Table 3.2, the EXXX value for the Coordinator means this report argues for the relationship between Extraverted and Coordinators but it is silent about the three other dimensions. The rightmost column of Table 3.2 indicates the degree of commonality among the other four studies. We designate the agreement points in the rightmost column if, for a given Belbin role, at least two of the studies agree on an personality as measured by MBTI dimension for that role.

Table 3.2: Studies on the relationship of personality and BTRs

Belbin roles (Belbin, 2012)	**Henley report** (Higgs, 1996)	**Stevens report** (Henry & Todd Stevens, 1999)	**Schoenhoff report** (Schoenhoff, 2001)	**MTR-I** (S. Myers, 2002)	**Agreement points**
Coordinator	EXXX	XSXX	ENFP	ESFP/ESTP	EXFP
Shaper	EXXX	EXXX	XSTJ	ESFP/ESTP	ESTX
Plant	IXTX	XNTP	INTJ	INTJ/INFJ	INTJ
Monitor Evaluator	IXTX	XXXX	ISXJ	ISTJ/ISFJ	ISTJ
Implementer	XXXX	XSXJ	ISXJ	XXXX	XSXJ
Resource Investigator	EXXX	EXXP	ENFJ	ENTP/ENFP	ENFP
Team Worker	EXXX	XXXX	ISTJ	ESFJ/ENFJ	ESXJ
Completer	IXXX	XSXJ	ISTJ	XXXX	ISXJ
Specialist	XXXX	XXXX	XXXX	ISTP/INTP	XXXX

3.1.3 Proposed Team Performance in Software Projects

Since there is widespread recognition of the role of the Myers-Briggs Type Indicator (MBTI) (Myers et al., 1985) and Belbin Team Roles (BTRs) (Belbin, 2012) with respect to team performance, in this section, we formulate a performance computation mechanism for software development projects by taking into consideration employees' personalities and skills. The motivation for the computational model is based on the previous findings and from both MBTI and BTR studies.

Belbin suggests two main factors for forming a team: *dyadic relationships of team members* and *competency* of team members in the tasks (Belbin, 2012). In this connection, we describe a formal model that represents the assignment of people to the software projects and which reflects the literature about team formation. In order to identify the rules and factors that affect team performance, we reviewed the previous studies. In the literature several investigations reported that some factors and rules can determine team performance (e.g. André et al. 2011). This computational model has some shortcomings and the essence of this chapter is not to present the results but to show how a team formation model can play a role in the team's performance. As we discuss in the discussion on the limitations of this thesis, the proposed computational model can be improved and validated by using a Delphi method and having consultations with experts in the software development domain. Managers calculate the performance of each team composition and select the best one for their task. The general formula for calculation of team performance is expressed as follows.

$$Performance = \text{Personality}\_composition * Competency \tag{3.1}$$

$$Personality\_composition = (\text{c1} * Matching\_Personality + \text{c2} * Matching\_roles + \text{c3} * Creativity + \text{c4} * Urgency + \text{c5} * Sociality + \text{c6} * Complexity + \text{c7} * \text{Belbin}\_Creativity + \text{c8} * \text{Belbin}\_Urgency + \text{c9} * \text{Belbin}\_Sociality + \text{c10} * \text{Belbin}\_Complexity) \tag{3.2}$$

To express this more compactly, we can write this as

$$Performance = (c_1*Pm + c_2*Rm + c_3*Cr + c_4*Um + c_5*So + c_6*Co + c_7*Bcr + c_8*Bum + c_9*Bso + c_{10}*Bco\ ) * c_{11}*C \tag{3.3}$$

The various parameters, such as *Matching_personality, (Pm), Matching_roles (Mr) ,…, C (Competency)* are explained and formulated in the next sections. These variables are numerical values that can be uniformly taken to be measured along some scale, such as 0 to 1 and each one is explained in the following sections. The identifiers c1,.., c11 are coefficients that can be adjusted for fitting empirical measurements. In this formulation for team performance, we have considered the factors that were most prevalent from our literature survey such as (Belbin, 2012) (Chen, 2005)(Bradley & Hebert, 1997) and (Myers, 1985). Further variables of our model are described as follows:

m: the number of skills required for the tasks

n: the number of employees for each team

R_k: the skills requirement vector for task k. Thus $R_k = [R_{k1}, R_{k2}\ldots,R_{km}]$

im: an index identifier indicating the most important skill

$R_k[im]$: the skill requirement of the most important skill for the task k

S_i: the skills vector of employee i. $S_i = [S_{i1}, S_{i2}, \ldots, S_{im}]$

As can be seen in Formula 3.2 we assumed that 10 factors play a role in the performances of teams which are matching personality, matching roles, creativity, sociality, complexity, Belbin creativity, Belbin urgency, Belbin sociality and Belbin complexity. These factors will be explained in Section 3.1.4.

3.1.3.1 Skill Competency of Team Members (C)

An important factor is the competency or skills of the team. We calculate the competency for each skill by dividing the skill of an employee by the skill requirements for the task. The overall team competency is the sum of all the team members' competencies for each skill.

In practice, managers have various preferences for task allocation. The standard approach is to find the minimal difference between the skills of employees and the task demands, and it is used in different ways in the literature for personnel selection (Canos & Lourdes, 2004). However, existing methods have not considered positive and negative gap values in connection with the differences. In order to evaluate various team formation mechanisms, we propose a similarity measure such that a positive gap value is considered as over-competency and a negative value is considered as under-competency. These two methods are presented as two different task allocation strategies. For each strategy, the manager will calculate a utility (i.e., skill competency of a team) and choose the team with the highest value.

3.1.3.2 Minimizing Under-competency

In this method, the main purpose of the manager is minimizing under-competency in assigning the task to the employees. The manager tries to choose the best combinations of employees who have the least under competency in their skill. They calculate the utility of teams based on the Formula 3.4, where C_{il} represents the competency of employees in the skill in this mechanism, R_l represents the skill requirement of task l, and S_{il} represents the skill of employee i in task l.

$$C_{il} = 1 - \max(\, 0,\ (R_l - S_{il})/R_l\,) \tag{3.4}$$

When task l requires multiple tasks the average competency of employee i determines her/ his score and the employees with the highest score are selected. As an example, assume that the task requires only one skill and R_l is 0.8 and S_{il} is 0.6 and the score for employee i is 1 – max (0, 0.2/0.8) = 0.75.The employees with the highest scores will be selected for the task.

3.1.3.3 Minimizing Over-competency

In this method, the main purpose of the manager is minimizing over-competency in assigning the task to the employees. The manager tries to choose the best combinations of employees who have the least over-competency in their skill. So they calculate the utility of teams based on the formula 3.5. C_{il} represents the competency of employees in skill in this mechanism.

$$C_{il} = \begin{cases} 1 - \frac{(S_{il} - R_l)}{R_l} & if\ S_{il} - R_l \geq 0 \\ 1 - \frac{(R_l - S_{il})}{R_l} & if\ S_{il} - \boldsymbol{R_l} < 0 \end{cases} \tag{3.5}$$

3.1.4 Personality Composition

The first ten factors in Formula (3.3) are related to the personalities of team members. We measure the goodness of team composition by factors such as matching their Belbin's roles, matching their personality as measured by MBTI, team creativity, the MBTI capability of teams in dealing with task requirements such as creativity, urgency, sociality, and task complexity, and the Belbin capability of the team to deal with task requirements such as creativity, urgency, sociality and task complexity. These factors which are summarized from previous works such as (Belbin, 2012) (Chen, 2005)(Bradley & Hebert, 1997) and (Myers, 1985) are described as follows:

Matching roles (Rm) : The term *Matching roles* represents the degree to which Belbin roles are suitably matched in a team. All the people have a primary natural team role that affects their behavior with each other. The interactive relationships of team members influence the team environment and performance. For example, if someone is aggressive towards someone, the recipient may respond by being diplomatic or by having a significant clash with the aggressor. Belbin's study shows this interpersonal relationship and what kind of people have higher likelihood to conflict with each other and what kind of people tend to work well with each other. In Table 3.3, we summarize these interpersonal relationships from Belbin's work (Belbin, 2012). Table 3.3 shows which combinations of team roles work well with each other and which combinations have a potential for conflict. For example, the first row shows that someone with a Shaper role works well with someone with a Resource Investigator role and there might be conflict with a Plant role.

On the basis of these relationships, we formulate the index *Rm* as an indication of relationship compatibility:

$$Rm_b = \frac{(Ps_b - Pu_b)}{\max[Ps_b, Pu_b]} \tag{3.6}$$

Where Rm_b is the degree of matching of peers' roles in team b, Ps_b is the number of suitable roles in the team, and Pu_b is the number of unsuitable roles in the team. For example, if we have a team with three suitable roles and one unsuitable role the $Rm_b = (3 - 1)/3$ = 0.66.

Table 3.3: Belbin's roles - suitable and unsuitable peers (Belbin, 2012)

Role	Suitable Peer	Unsuitable peer
Shaper	Resources Investigators	Plant
Specialist	Implementers, Team Workers	Plant
Monitor Evaluator	Coordinators, Implementers	Completers, Other Monitor Evaluators
Completer	Implementers	Resource Investigators
Implementer	Coordinators, Monitor Evaluators, Resource Investigators, Completers and Specialists	Other Implementers and plants
Resource Investigator	Implementers and Team Workers	Completers and Specialists
Coordinator	Implementers and Team Workers	Shapers
Team Worker	Other Team Workers and Plants	Shapers

Matching index (Pm) : Matching-index (Pm) represents the degree to which personalities, as measured by MBTI type, are matched. We base this on studies about the effect of personality composition of a team. As with Belbin's roles, some personalities do not get along well with each other, so it can be important to configure team personalities appropriately **(Chen, 2005).** We have surveyed the literature concerning personality composition of teams, and Table 3.4 shows the relationship conflicts across personality as measured by MBTI types. These assumptions are based on several works ((Chen, 2005)(Bradley & Hebert, 1997) (Culp & Smith, 2001)).

Table 3.4: Relationships of personality as measured by MBTI dimensions

	T	F
T	0	+
F	+	0

	J	P
J	+	-
P	-	+

	E	I
E	-	0
I	0	0

	S	N
S	0	+
N	+	0

Note that in the table, '+' means that there is a positive effect, '-'means there is a negative effect, and '0' means that there is no effect.

It has been found, for example, that two extraverted (EE) people working together can be problematic because they can be dominant and assertive towards each other. In Table 3.4, we can see that two Extraverted (E) people have a negative effect. Additionally, it has been found that contrasting Sensing and iNtution types (SN) can be useful to each other, as well as contrasting Feeling and Thinking (FT). Sensing(S) and iNtution (N) have a positive effect on each other as well as Feeling (F) and Thinking (T) types. People who differ across the Judging and Perceiving (JP) dimension tend to frustrate each other, but people at the same end of the Judging or Perceiving scale have similar interests and can understand and predict each other's behavior. It can be seen in Table 3.4 that matching Judging (J) types with another Judging (J) type has a positive effect. Matching Perceiving (P) types with another Perceiving (P) type has a positive effect and matching Judging (J) types with another perceiving (P) type has a negative effect.

The scale of personality as measured by MBTI is set between 0 and 100. In order to make the maximum and minimum value for all of these factors consistent, the formula for EE_{ij} that is the sum of two personalities is different from the other formulas. The maximum possible values for all of these factors are 0.5.

$$EE_{ij} = \begin{cases} \frac{(EI_i + EI_j)}{200} & if \ \ EI_i < 50 \ and \ EI_j < 50 \\ 0 & otherwise \end{cases} \tag{3.7}$$

$$NS_{ij} = \begin{cases} \frac{[(NS_i - NS_j)]}{100} & if \ \ NS_i > 50 \ and \ \ NS_j \leq 50 \\ & or \ \ NS_i \leq 50 \ and \ \ NS_j > 50 \\ 0 & otherwise \end{cases} \tag{3.8}$$

$$TF_{ij} = \begin{cases} \frac{[(TF_i - TF_j)]}{100} & if \ \ TF_i > 50 \ and \ \ TF_j \leq 50 \\ & or \ \ TF_i \leq 50 \ and \ \ TF_j > 50 \\ 0 & otherwise \end{cases} \tag{3.9}$$

$$JP_{ij} = \begin{cases} \frac{(JP_i + JP_j)}{200} & if \ JP_i > 50 \ and \ \ JP_j > 50 \\ \frac{(100 - JP_i) + (100 - JP_j)}{200} & if \ JP_i \leq 50 \ and \ \ JP_j \leq 50 \\ -\frac{[(JP_i - JP_j)]}{100} & if \ \ JP_i > 50 \ and \ \ JP_j \leq 50 \ \ or \\ & JP_i \leq 50 \ and \ \ JP_j > 50 \end{cases} \tag{3.10}$$

Using these parameters, we construct the final score for matching personality between employee i and employee j by taking the average of matching personalities in all four dimensions. So, we have:

$$Rp_{ij} = \frac{(-EE_{ij} + \boldsymbol{NS_{ij}} + TF_{ij} + JP_{ij})}{4} \tag{3.11}$$

Where Rp_{ij} represents the matching personality between i and j. In order to take into account all the members of a team, we calculate the average of matching indexes in the four dimensions. So, matching personality of a team is expressed as follows:

$$Pm_b = \frac{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} Rp_{ij}\right)}{n} \tag{3.12}$$

In the above formulas, EE_{ij} represents the dyadic effect of the Extraverted-Introverted dimension, SN_{ij} represent the dyadic effect of the Sensing-iNtuition dimension, TF_{ij} represents the dyadic effect of the Thinking-Feeling dimension, and JP_{ij} represents the dyadic effect of the Judging-Perceiving dimension. Pm_b indicates the matching personality of team b. As an example, let's say, we have a team consists of two members who are ISTJ and ESFJ, their EE_{ij}, NS_{ij} and JP_{ij} are zero (because we have none of these combinations) and the TF for the first agent is 40 and for the second one is 60 according to the above formulas (3.9) TF is [40-60] / 100 = -0.2 and according to the formulas 2.11 and 3.12 Pm_b is $\frac{(0+0+0+0.2)}{4} = 0.05$.

So far, we have just considered how personalities and roles match with each other, but we must also take into consideration how they match up with the task types. To operationalize this, we consider various tasks to have different levels with respect to (a) required creativity, (b) urgency, (c) required social interaction, and (d) complexity. Each of these categories is discussed further below. In this connection, we use Team Personality Elevation (TPE) and Team Personality Diversity (TPD) that are useful for these considerations (Bowers et al., 2000), as discussed in Chapter 2.

Creativity (Cr): For tasks requiring a high level of creativity, teams composed of differing attitude tendencies are believed to perform better than teams of like-minded people (Bowers et al., 2000). So here we assume high heterogeneity (high TPD) in the four personality dimensions will lead to creativity. Moreover, the creativity of individuals is related to their Intuition level (Bradley & Hebert, 1997). So, in addition to a high TPD in all four personality dimensions, we also assume that high TPE in Intuition has positive effects on creativity. In the following expressions, Cri_b is the combined team index for creativity, and Crr_k is the required creativity for the task.

$$Cr_b = (TPE \text{ of } Intuition + mean\ of\ TPD\ )/\ n * 100) \qquad (3.13)$$

$$Cri_b = \begin{cases} Cr_b/Crr_k & if\ \ Crr_k - Cr_b \geq 0 \\ 1 & if\ \ Cr_b - Crr_k > 0 \end{cases} \qquad (3.14)$$

$mean\ of\ TPD$ represents the average of TPD in four personality dimensions. Cr_b is creativity for team b and Crr_k ranges from 0 to 100.

Urgency (Um): When time is important, Perceiver types, who need freedom for their actions, are less likely to be successful. In contrast, Judgers relish getting in on the closure of a task, and so they can have a positive effect on tasks with time pressure (Myers, 1985). As a result, we believe that a high TPE in Judging has a positive effect in performing urgent tasks.

$$Um_b = (TPE\ in\ Judging\ /\ n)\ *\ 100 \qquad (3.15)$$

$$Umi_b = \begin{cases} Um_b/Umr_k & if \;\; Umr_k - Um_b \geq 0 \\ 1 & if \;\; Um_b - Umr_k > 0 \end{cases} \tag{3.16}$$

Umi_b is the combined team score (index) for Urgency, and Umr_k is the required Urgency for the task.

Sociality ($\boldsymbol{So}$): Sociality is the degree to which team members tend to interact and associate in teams. Having interactions with the other team members is a crucial factor in some tasks and extraverted individuals can help the team in such tasks (Myers, 1985)Therefore, we assume a high TPE in Extraversion has a positive effect in performing these tasks.

$$So_b \; = (TPE \; in \; \text{Extravterted} \; /\text{n}) \; * \; 100 \tag{3.17}$$

$$Soi_b = \begin{cases} So_b/Sor_k & if \;\; Sor_k - So_b \geq 0 \\ 1 & if \;\; So_b - Sor_k > 0 \end{cases} \tag{3.18}$$

Soi_b is the combined team score for Sociality, and Sor_k is the required sociality for the task.

Complexity ($\boldsymbol{Co}$): When the complexity of a task is high, a rational and scientific mind that is characteristic of Thinking types can be useful. As a result, we expect a high TPE in Thinking will have a positive effect in performing these tasks.

$$Co_b \; = (TPE \; in \, Thinking \; / \; n \,) * \; 100 \tag{3.19}$$

$$Coi_b = \begin{cases} Co_b/Cor_k & if \;\; Cor_k - Co_b \geq 0 \\ 1 & Co_b - Cor_k > 0 \end{cases} \tag{3.20}$$

Coi_b is the combined team score for complexity, and Cor_k is complexity of the task.

In addition to the above eight indicators, we assume that some roles are crucial for some tasks, so we have introduced the following constraints based on Belbin's findings (Belbin, 1981). Having:

- At least one Plant is essential for tasks with a high creativity requirement.
- At least one Completer is essential for tasks with a high urgency requirement.
- At least one Evaluator is essential for tasks with a high complexity requirement.

- At least one Resource Investigator is essential for tasks with a high complexity requirement.

Regarding the above mentioned rules and constraints which have been extracted from the literatures on team performance and personality, we develop an agent-based model for task allocation. We have used optimization and filtering algorithms to compute the utility of all the combinations. The system searches for all the possible combinations of a team and calculates the highest valued coalition as presented in Formula 3.1. The system then assigns tasks to the employees to maximize the utility of the system. The following algorithm presented in Figure 1 is used for the highest valued coalition U^* and by computing the formula presented in Formula 3.3, different compositions of teams are ranked and the best one is selected. The algorithm can be used for teams with different sizes. A schematic algorithm that is used for this experiment is presented in Figure 3.2.

3.1.5 The Model to Evaluate the Effect of the Task Allocation Mechanism on Team Performance

Wood (1986) argued that task dynamics that refer to the changes in the complexity of tasks have an effect on the relationship between task inputs and products. Zoethout et al. (2007) studied the influence of task variety on the behavior of specialists and generalists. Jiang et al. (2010) examined how the change in a task requirement dynamically affects individual behavior. In these studies, the effect of the team formation mechanism is not fully covered.

In order to explore the effect of the team formation mechanism of our model on the proposed task allocation mechanism in which tasks are dynamic, we conducted some simulation experiments on the NetLogo platform (Tisue & Wilensky, 2004).

In reality, tasks have a dynamic nature and their requirements change over time. Therefore the effect of task dynamics on teamwork must be taken into consideration. To do so, after describing a general approach to select effective team members based on their personalities and skills, we consider as an example a comparative multi-agent simulation study contrasting two different sample strategies that managers could use to select team members by: 1) minimizing team over-competency and 2) minimizing team under-competency. Based on the simulation results, we derive a set of propositions about the conditions under which there are and are not performance benefits from employing a particular strategy for task allocation. Also, we propose a simulation environment that could provide a low cost tool for managers and researchers to gain better insights into the effectiveness of different task allocation strategies and employees with different attributes in dynamic environments.

In this process that is depicted in Figure 2, the dynamic tasks are characterized by changing the requirements of the tasks. In reality, teams have to reschedule their projects because of new requirements for tasks. Rescheduling has some cost, since it takes time for new members to be familiar with the new tasks, and it causes some dissatisfaction for those who leave the task. In each time step, with a certain probability, the requirements of one skill increase, and managers select the best team for this task. So in each time step managers calculate the payoff of changing teams, and if this payoff is positive, they change the team. This payoff is calculated by the following formula:

$$Payoff = \left(\sum_{i=1}^{n} C_{inew} - C_e t \right) - \sum_{i=1}^{n} C_{icurrent} \tag{3.21}$$

Where C_{inew} and $C_{icurrent}$ represent the competency of new and current team members respectively.

The cost of changing a team is a constant number and is indicated by C_e. The cost, of changing the current team, is formulated by $C_e t$. This cost is related to the time that has elapsed from the starting point of the project. As a result, the skill competency of the team that is presented by Ds_{bk} is calculated according to the following formulae.

$$Ds_{bk} = \begin{cases} \sum_{i=1}^{n} C_{inew} - C_e t & if \ \left(\sum_{i=1}^{n} C_{inew} - C_e t\right) > \sum_{i=1}^{n} C_{icurrent} \\ \sum_{i=1}^{n} C_{icurrent} & if \ \left(\sum_{i=1}^{n} C_{inew} - C_e t\right) \le \sum_{i=1}^{n} C_{icurrent} \end{cases} \tag{3.22}$$

$$Performance(t) = Ds_{bk} * PC_b * T \tag{3.23}$$

Where $Performance(t)$ indicates the performance of team in time T, PC_b indicates the personality composition of team b and is calculated as presented in Formula 3.2.

In the experiments, we compare the performances of two managers who assign the employees to the tasks. In order to calculate the competency C_k, the manager with the "Minimizing Under-competency" strategy uses Formulas (3.1) and (3.4) and the manager with the "Minimizing Over-competency" strategy uses Formulas (3.1) and (3.5).

This flowchart is presented in Figure 2. In the initial settings, the environment had 12 employees and four tasks. In this connection, a task role is assigned to each person, and the choice for this role is guided by the personality information from Agreement Points (right-hand-most) column of Table 3.2. Values between 0 and 10 are assigned to the employees (these skill levels are assigned according to a normal distribution with a standard deviation of 3). In addition, specific task attributes are assigned to the task, such as the required level of creativity, social interactions, complexity, and urgency. Each task requires 100 time steps to be completed. Also, a number between 0 and 100 is assigned to each such task attribute such as Creativity, Sociality and so on. Three skills are allocated to the task representing the skills that are required, and a number between 0 and 10 represents the required skill level. For the sake of simplicity, we assume that all teams comprise a small number (three) of employees. Also, in the simulation settings, number 1 is assigned to $C1$,..., $C11$ in Formula 3.3. Note that our formulae involving required skills and actual employee skills always involve ratios of these entities. Thus the scale (zero to a maximum value) of these parameters can be arbitrary, as long as the scale is held to be the same for all the relevant parameters in the formula. For simplicity, we have chosen the scale to be from 0 to 10 for these parameters." Establishing a skill range of between 0-100 is a common approach and can be seen in other similar studies (e.g. Zhang, 2007). The selected range is a compression version of their range.

1. $V \leftarrow$ *set all the possible task order*

2. ***For each*** *order*

3. $C \leftarrow$ *set all the combinations of employees*

4. $U_j \leftarrow$ *set the utility of each employee combination with task j*

   based on mangers' task allocation strategy

5. $U_j^* \leftarrow$ *set the maximum of* U_j

6. $U_{max} \leftarrow argmax\ U_i^*$

7. ***if*** $employee_i \in U_{max}$ and

   it doesn't violate any constraints about task j

8. ***then*** *compute the effeciency of* U_{max} *with formula* (3.3)

9. *Delete all the combinations in C that contain employee i*

10. ***if*** *C is not empty*

11. ***then*** *goto* 2

12. ***else*** *Calculate*: $Z \leftarrow \sum U_{max}$

13. *Choose Max Z*

14. ***Return***

Figure 1: Task allocation algorithm

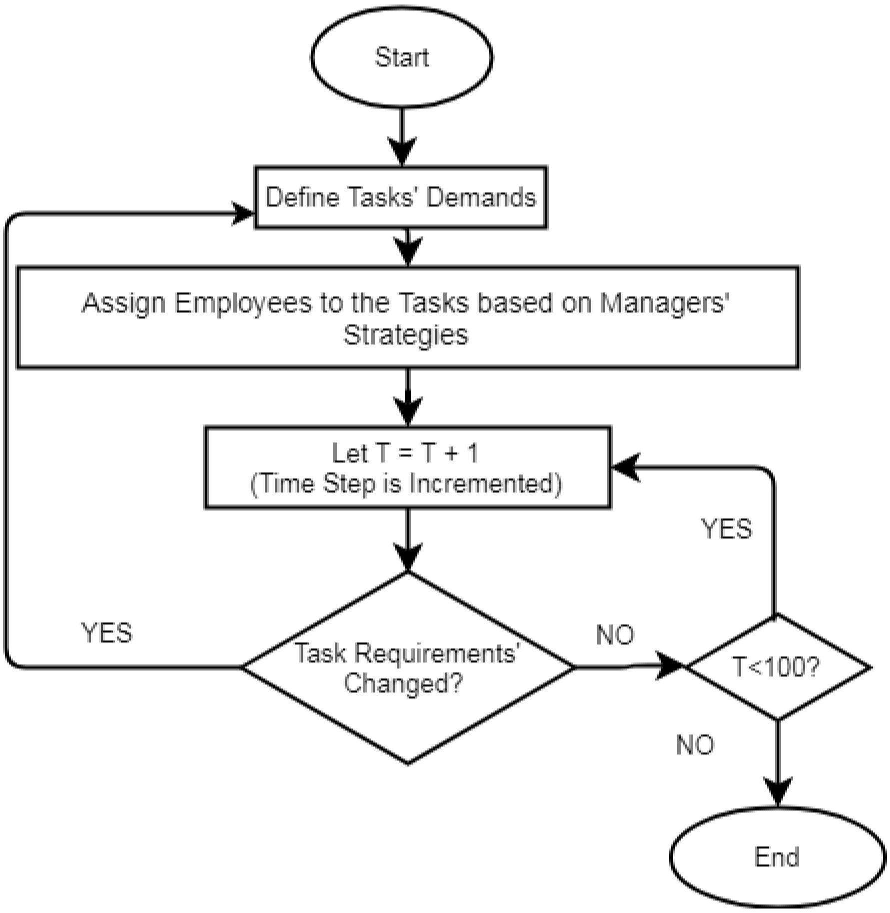

Figure 2: Staff allocation algorithm

The results of simulation experiments are summarized in Figure 3. It compares the simulation results of the two task allocation methods with different probabilities of increasing the task requirements in each time step. The results are averaged over 100 runs of the model.

The results revealed that by increasing the chance of changes in the task requirements, the performance decreases for both task allocation mechanisms. In the beginning, when the dynamic level of tasks is not significant, the under-competency mechanism outperforms the over-competency mechanism. However, after increases in the dynamic level of tasks, the over-competency mechanism ended up with a better performance compared to the under-competency mechanism. This phenomenon illustrates some interesting features, such as the importance of employing task allocation mechanism regarding the characteristics of the tasks and environment.

As a result, we conjecture that the strategy that managers employ for allocating staff to a team is a key factor for team performance. A simple, approximate explanation of this behavior can be as follows.

According to the results, in a dynamic environment the under-competency mechanism ended up with a worse performance compared to the over-competency mechanism. The reason for that can be that in the real world when the probability of changes in the task requirement is small, managers who minimize over-competency are more likely to make mistakes. For instance, among two employees where one is overqualified, and another one is underqualified, over-competency managers might choose the underqualified one that will result in poor performance. When the probability of changes in the task requirement increases, we conjecture employee selection among some overqualified employees is a random process for managers who minimized under competency. In these circumstances, in order to perform the upcoming projects, some previously selected overqualified workers are required. However, those workers are already busy with some tasks that could be performed with some less skilled workers. As can be seen in Figure 3, this phenomenon occurs more in a dynamic environment and results in some costs for managers that choose under-competency strategy.

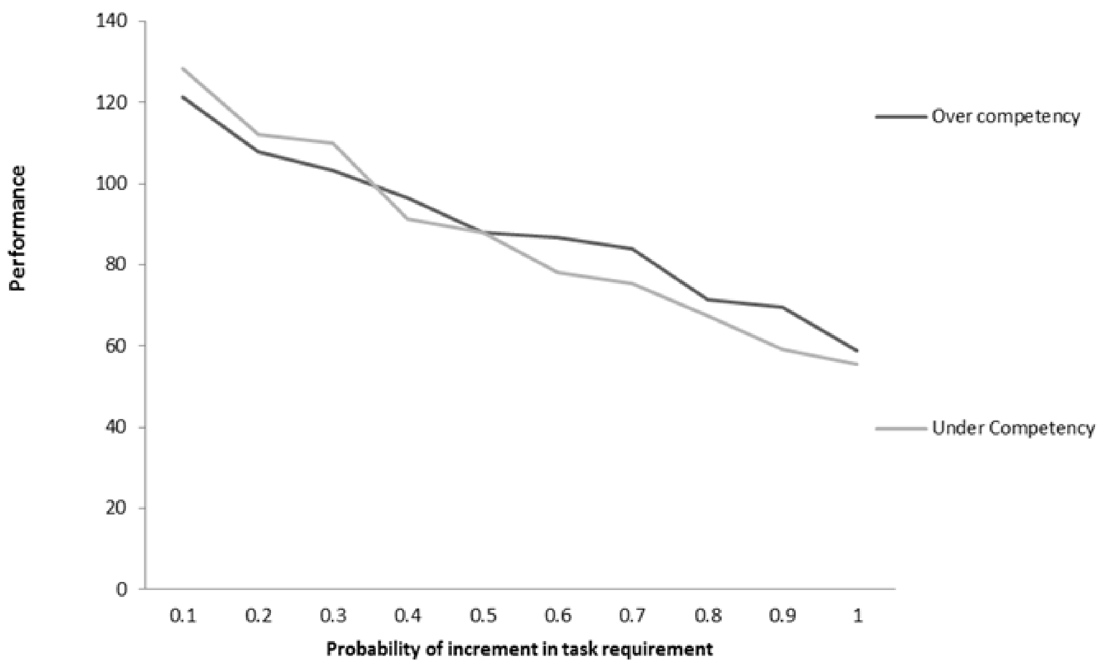

Figure 3: Task allocation mechanism and tasks with dynamic requirements

In order to understand the relationship between personality and dynamic tasks, we conducted further simulation experiments. In the previous experiments, we assigned random personalities to the employees. In contrast, in these experiments, some scenarios are evaluated with respect to various personality configurations. We examined the performances of members with different distributions of personality when the probability of changing the requirements of the task in each time-step is 0.3. In other words, we are interested in examining whether a task allocation mechanism has any advantages over another one for a particular personality distribution.

In order to assess the robustness of each personality distribution and qualify the certainty of predictions arising from experiments, we used a *one-at-a-time* uncertainty analysis technique, the Vargha-Delaney A-test (Vargha & Delaney, 2000), which is a non-parametric effect magnitude test, to determine when a parameter adjustment has resulted in a significant change in simulation behaviour from the baseline. The test compares two population distributions and returns a value in the range [0.0, 1.0] that represents the probability that a randomly chosen sample taken from the population A is larger than a randomly chosen sample from population B. Table 3.5 shows how the A-test scores relate to various magnitudes of differences between two populations. For this simulation test baseline behaviour is required, and we used here the personality distribution when personalities are assigned randomly. For instance, an A-Score that is 0.38 means a medium difference.

Table 3.5: The magnitude effect by A-test score

Differences	Large	Medium	Small	None	Small	Medium	Large
A score	0.29	0.36	0.44	0.50	0.56	0.64	0.71

In our experiments, we have 20 scenarios; each scenario represented a different personality distribution, and the results are summarized in Table 3.6. In each scenario, we measure the probability that the under-competency mechanism performs better than the over-competency mechanism.

For instance, the first number in the left-top of the Table 3.6 is 0.391. This number means in the case that 0% of employees are introverted, and 100% are extraverted the probability that under- competency mechanism performs better than over -competency is 0.391.We found that the magnitude of the performance advantages depends not only on the personality distribution, but also on task allocation strategy. In most of the cases (different distributions of personality), there were none or only a small magnitude effect measured by the A-Test score between task allocation mechanisms. In most of the scenarios, the probability of having a better performance with under-competency mechanism is slightly better than the other task allocation mechanism. However, we observed in some scenarios the over-competency mechanism outperformed the under-competency mechanism with a medium magnitude effect. For example, when 100 % of the employees have Judging type, the A-score is 0.581, which means the probability that the over-competency performs better than under-competency is 0.581. In general, the over-competency mechanism had slightly better performances in cases when the majority of employees were more Feeling or more Perceiving or more Sensing or more Extraverted.

These observations are interesting and can be explained approximately. For instance, when the majority of employees are Extraverted, minimizing over-competency more likely saves some of the capabilities of the organization for the next projects with a high sociality requirement.

Table 3.6: Different personality distributions and team formation strategy

	I-E	N-S	T-F	J-P
0%-100%	0.391	0.53	0.578	0.312
25%-75%	0.432	0.522	0.504	0.366
50%-50%	0.476	0.513	0.451	0.397
75%-25%	0.493	0.43	0.424	0.492
100%-0%	0.545	0.37	0.405	0.581

In summary, the model indicates that the team formation mechanism is an important component for predicting team performance. This factor is even more crucial when teams are self-assembly teams and are dynamic (i.e. changes to team composition are allowed).

3.2 Conclusion

In this chapter, we investigated the impact of task allocation strategies on team performance, in the software projects. In this connection, by reviewing previous findings from MBTI and

Belbin Team Roles, we developed a computational model to measure the performance of teams. In our experiments, we compared two team formation mechanisms and their effects on the team performance in a dynamic environment. Two team formation mechanisms which are called *minimizing under competency* and *minimizing over competency* were compared to investigate the effect of team formation mechanism on team performance.

In the experiments, it was argued that the strategies that managers employ for allocating staff to a team are key factors for team performance. The experiments revealed that by increasing the likelihood of changes in the task requirements, the performance became poorer.

Moreover, in order to understand how the personalities of employees mattered in our experiments, we examined the performances of members with different distributions of personality. In most of the scenarios, the probability of having a better performance with the under-competency mechanism was slightly better than another task allocation mechanism. However, it was observed in some scenarios (for example, when 100% of employers have Perceiving personality) that the over-competency mechanism outperformed the under-competency mechanism with a medium magnitude effect.

CHAPTER 4

4 TEAM FORMATION MODEL IN COLLABORATIVE LEARNING

In the previous chapter, we demonstrated the effect of team formation mechanism on team performance in an environment where team members have no autonomy on selecting their team members.

In order to analyze an environment in which team members have more autonomy in selecting a team, in this chapter, we describe the development of an agent-based modelling approach that can assist in understanding the *collaborative learning* of project teams. In other words, we argue how different mechanisms for selecting teammates influence the collaborative learning and consequently team performance.

While collaborative learning has long been believed to hold a great value for organizations and classrooms (Khandaker & Soh, 2010), modelling this learning in small, short-term project teams has not been studied in past research. A key aspect of the presented approach is our *distinction between knowledge and skills required for the achievement of project goals*. Both of these forms of intelligence (knowledge and skills) need to be learned in the project context, but the rate of their expansion or enhancement may proceed differently, depending on the personality makeup of the team and the mechanism employed for team assembly.

Based on reports from the theoretical and empirical literature, we derive a multi-agent computational model that characterizes how knowledge and skills may be learned among team members with varying personality attributes. Also, group formation in virtual learning environments is either done voluntarily by students or with the support and recommendations of the system. In this connection, we studied two types of group formation mechanisms in self-assembly teams and the role of each mechanism in collaborative learning and performance of teams. The results from this model are published in (Farhangian et al., 2015 b).

In this model, we describe our agent-based model that incorporates personality type along with the knowledge and skill levels for each agent. The personality type is assumed to be fixed while the knowledge and skill levels are dynamic. In this model, we investigate how the team formation mechanism influences collaborative learning and consequently team performance.

Unlike traditional teams where employees learn and improve their performance through formal training, in many modern projects, collaborative learning within small teams often is undertaken and these teams may be assembled only for specific, short-term tasks. There has been growing interest in the virtual learning communities and how groups of students enhance their learning using Computer-Supported Collaborative Learning (CSCL) environments in which students form various study groups and learn subjects together (Khandaker & Soh, 2010). How well these teams collaborate and fulfill their missions will depend on the personalities of the individual team members and how well they can share their knowledge and skills. In this work, we discuss how team formation mechanisms are involved in the acquisition and retention of skill and knowledge.

In the context of team learning, we believe that there is a significant difference between knowledge and skill (Purvis, 2012). Knowledge, which can be characterized as "know-what", is articulable, i.e. it can be expressed in linguistic form and transmitted to others relatively easily. On the other hand, a skill, which can be characterized as "know-how", refers to a capability of effective interaction with the environment via a tight feedback loop. Skills, for example, the skill of riding a bicycle, are not easily put into words, since they involve tight feedback loops with the environment; and hence they are not as easily transferred when compared to knowledge (Anderson et al.,1997). To learn a skill often requires close observation and collaboration with a master who already has the skill (Anderson et al., 1997).

Collaborative learning is a learning method that helps people to retain, transfer, and receive knowledge and skill through intra-group collaboration and competition between groups (Chen & Yang, 2014). The knowledge necessary for performing a task may be declarative, procedural, or a mixture of these two. Declarative knowledge represents factual information; procedural knowledge indicates task knowledge. For example, in the case of the learning of riding bicycle, how brakes work is considered as declarative knowledge and using a brake when riding a bicycle is considered as procedural knowledge (Anderson et al., 1997).

Today agent and agent-based services facilitate collaborative learning in crowdsourcing platforms and Computer-Supported Collaborative Learning (CSCL) environments. Agents can provide decision support for managers or teachers and assist them for some tasks, such as group formation. Designing a real multi-agent tool often entails high cost, time and effort. Hence, we simulate collaborative learning to analyze the effect of attributes such as the team formation mechanism and personality on the performance, knowledge, and skill growth of team members. The existing simulation models and tools presented in several research works (such as Spoelstra & Sklar, 2007 and Khandaker & Soh, 2010) do consider personality in conjunction with knowledge and skill and considering these aspects forms the main focus of this model.

ACT-R (Anderson et al.,1997) is a cognitive model that provides mechanisms for representing procedural and declarative knowledge learning and forgetting. We chose to use ACT-R to represent employees' or learners' memory for acquisition and retention of declarative and procedural knowledge, because other similar architectures such as SOAR (Laird, 1987) and EPIC (Kieras & Meyer, 1997) are more restricted. SOAR does not provide a forgetting mechanism, and EPIC does not provide a rule-learning mechanism. A complementary approach to the cognitive approach, such as in the studies above, is to apply agent-based models to simulate human behavior (Martínez-et al. 2009). In this work, we employ the ACT-R model for individual agents who interact with each other in a social setting.

Teams may benefit from the way they share information and collaborate, and this aspect of project team performance – how it evolves given the circumstances of personality makeup, skills, and knowledge – has not been explored to a large extent. This model demonstrates the key role of understanding the mechanism behind team formation in collaborative learning and consequently in team performance. In this work, by employing ACT-R as an architecture that deals with the emulation of human mental processes in conjunction with our proposed agent-based model, we describe and simulate our study in this area.

4.1 The Model

Figure 4 shows a schematic diagram of an individual agent that works on a project team. It has personality, skill, and knowledge components. Within the knowledge, there is the

"Knowledge Credibility" subcomponent, which stores the confidence in which knowledge sources and interactive partners are held.

The goal is to use this model as a modifiable template for the examination of dynamic knowledge and skill influences on individual and team performance via simulation experiments. Agents are seeded with various personality types, knowledge, and skills (as described below), and then simulations are run to examine collaborative learning. For each simulation cycle, agents team up and start working on a task. They exchange what knowledge they have with teammates and update their Knowledge-Credibility values with respect to their teammates. They also improve their skills by observing and imitating their teammates' behaviours.

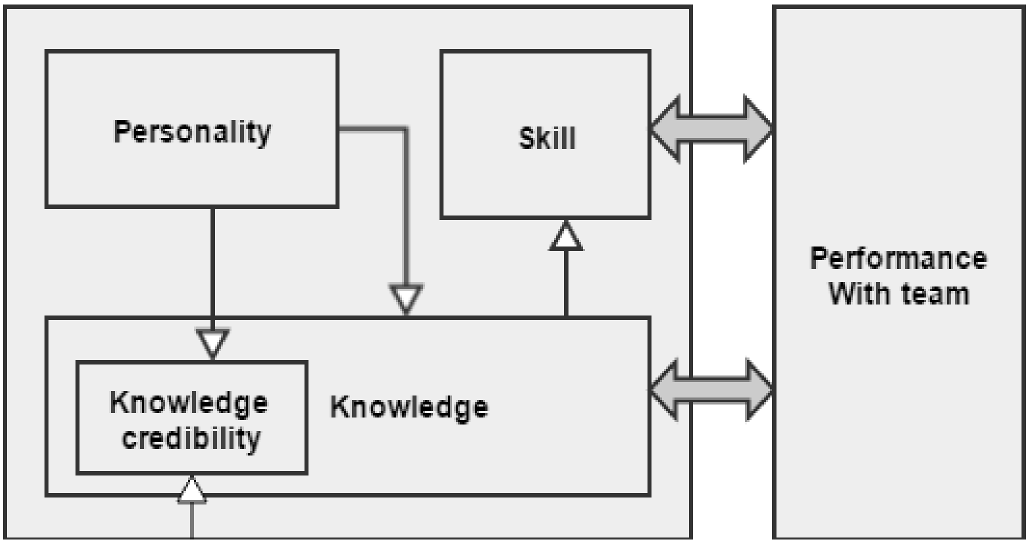

Figure 4: Collaborative Learning model components' overview

As can be seen in Figure 4 performance of a team depends on the skill and knowledge of team members and learning of these skills and knowledge both directly and indirectly depends on the personality of team members. In the following subsections, further details concerning the operation of these agent components are provided.

4.2 Task Performance

In our model, each group task needs a set of knowledge and skills. *TASK* is a set of tasks that we have in the system.

$$TASK = \{task_1, task_2, \dots, task_n\} \quad (4.1)$$

And each $task_b$ is a vector of l- dimensions; each dimension represents the requirements for that task. And each $task$ requires a vector of skill requirements:

$$REQ_b = \{requirement_{b1}, requirement_{b2}, \dots, requirement_{bn}\} \quad (4.2)$$

For example, we have a task that is about analyzing health data in New Zealand. It requires a set of skill requirements as presented as follows:

$$REQ_1 = \{RProgramming, presentation\} \quad (4.3)$$

Completing a task requires two sets of knowledge (general knowledge and skill-related knowledge). Before the acquisition of one skill, one needs to learn a knowledge set related to that skill:

Here K_{rvb} represent the knowledge matrix related to skills for task b.

$$K_{rvb} = \begin{bmatrix} \mathrm{k}_{rb11} \ \mathrm{k}_{rb12} \ \dots \ \mathrm{k}_{rb1n} \\ \mathrm{k}_{rb21} \ \mathrm{k}_{rb22} \ \dots \ \mathrm{k}_{rb2n} \\ . \\ . \\ . \\ \mathrm{k}_{rbm1} \ \mathrm{k}_{rbm2} \ \dots \ \mathrm{k}_{rbmn} \end{bmatrix} \quad (4.4)$$

In our example, we need some knowledge about R programming and about presentation. The first row of the matrix K_{rvb} indicates the knowledge about R programming and each $\mathrm{k}_{rb11}, \mathrm{k}_{rb12}, \dots, \mathrm{k}_{rb1n}$ represents a fact. For example, k_{rb11} represents this knowledge: the micro benchmark library in R provides infrastructure to accurately measure and compare the execution time of R expressions. This knowledge which is about R programming has value 0 (for one who does not have this knowledge) or 1 (for someone who does have this knowledge). As another example k_{rb21}, k_{rb22} … k_{rb2n} are pieces of knowledge about Python. We should note that in this example the matrix have only two rows since there are only two skill requirements. However, if there are m skills there will be m rows.

Apart from these related-knowledge skills, for each task, some general knowledge is required that is represented with K_{gb}.

$$\mathrm{K}_{gb} = [\mathrm{k}_{gb1}, \mathrm{k}_{gb2}, \dots, \mathrm{k}_{gbm}] \quad (4.5)$$

In our example, where we need some pieces of information about the health economy in New Zealand, and each term in $\mathrm{k}_{gb1}, \mathrm{k}_{gb2}, \dots, \mathrm{kb}_{gbm}$ represents a fact. For example, k_{gb1} represents the knowledge that "there is a correlation between diet nutrition and income in the New Zealand".

In our model, each employee has a set of skills.

$$skill_i = \{skill_{i1}, skill_{i2}, \dots, skill_{in}\} \quad (4.6)$$

Each element in the set represented by $skill_i$ represents the qualification of employee i. For example, for employee 1, $skill_1$ represents his or her ability for a particular skill (e.g. programming). In this context, $skill_{11}$ represents ability to program in R and the value might be 0 (i.e. the employee does not have R skills) and $skill_{12}$ represents ability of programming in MATLAB and the value might be 5 (out of 10). The competency of members in skills is calculated as follows:

$$Sk_{il} = 1 - \min\ \{0,\ \ (skill_{il} - requirement_{bl})\}\ /\ skill_{il} \quad (4.7)$$

Sk_{il} indicates the competency of employee i in domain l; $skill_{il}$ indicates the level of skill of employee i in domain l; and $requirement_{bl}$ indicates the level of skill requirement in domain l in task b. For example, the domain can be presentation or programming. We used this formula to avoid giving credit to the employees' over-qualifications. The sum of the competency of employee i in task b is calculated by the sum of his competency in all the domains as follows:

$$Sk_{ib} = \sum_{l=1}^{m} Sk_{il} \quad (4.8)$$

Sk_{ib} represents the competency of employee i in task b, and m represents the number of domains in the task b for employee i. Also, each employee has some knowledge vectors for each skill that is represented as the following matrix:

$$K_{evi} = \begin{bmatrix} k_{ei11} & k_{ei12} & \dots & k_{ei1n} \\ k_{ei21} & k_{ei22} & \dots & k_{ei2n} \\ & & . & \\ & & . & \\ & & . & \\ k_{eim1} & k_{eim2} & \dots & k_{eimn} \end{bmatrix} \quad (4.9)$$

K_{evi} represent the knowledge vector related to each skill for employee i.

Apart from knowledge related to skill, each employee has two other knowledge vectors, including general knowledge and knowledge about other people.

$$K_{gi} = [k_{gi1}, k_{gi2}, \dots, k_{gim}] \quad (4.10)$$

K_{gi} represents the general knowledge vector of employee i. And K_{ij} in the following vector represents the knowledge of employee i about the knowledge credibility of employee j.

$$K_{ij} = [k_{i1}, k_{i2}, \dots, k_{ij}] \quad (4.11)$$

The final performance of the employees in the tasks is related to their skill competency and general knowledge competency. In our example the skills are R programming and presentation, and the knowledge is about health economy. These skills and knowledge together will determine the task performance. Knowledge competency is calculated as follows:

$$KK_{gib} = \max\{0, K_{gb} - K_{gi}\} \quad (4.12)$$

Where KK_{gib} indicates the general knowledge competency of agent i for task b. K_{gb} indicates the general knowledge requirements for task b and K_{gi} indicates the general knowledge of agent i. As having both knowledge and skill are critical for the performance of a task, the following formula is suggested for the team performance:

$$Pe_b = (\sum_{i=1}^{n} W_{si} * Sk_{ib}) * (\sum_{i=1}^{n} W_{ki} * KK_{gib}) \quad (4.13)$$

Pe_b indicates the performance of a team in task b, Sk_{ib} indicates the competency of agent i for task b, and KK_{gib} indicates the general knowledge competency of agent i for task b.

There are two weighting terms W_{si} and W_{ki}. W_{si} indicates the importance of skill i and W_{ki} indicates the importance of knowledge i.

In the rest of this chapter, we argue that skill and knowledge improve over time and demonstrate how the personalities of employees make a difference in employees' learning and teams' performances.

4.3 The Influence of Personality

In our model, there are three out of four personality dimensions (as specified by the MBTI scheme) that come into play. Associated with these three personality dimensions, six assumptions are considered and explained in Table 4.1. These assumptions are based on studies reported in the literature about MBTI and team behavior (Varvel, Adams, Pridie, & Ruiz Ulloa, 2004a), (Myers, Isabel Briggs, Mary H. McCaulley, 1985), (Capretz, 2003), (J. H. Bradley & Hebert, 1997), (Cruz, da Silva, & Capretz, 2015).

Table 4.1: Assumptions of Personality Influence on collaborative team learning

Assumptions of Personality Influence on collaborative learning
1. Compared to Feeling types, a Thinker's relationship with a person is more sensitive to their knowledge of that person.
2. Sensors record the result of their satisfying or unsatisfying team experiences as facts more than iNtuitive types do.
3. Sensors have a higher rate of gathering knowledge from others compared to iNtuitive types.
4. iNtuitive types have a higher rate of self-learning knowledge compared to the Sensors.
5. It is more likely for extraverted types to share their knowledge compared to introverted types.
6. Introverted types have a higher self-learning skill rate compared to extraverted types.

Apart from personality variables, some other non-personality variables affect decisions and behaviour. These factors include task performance, knowledge credibility, knowledge growth, skill growth and forgetting (of both knowledge and skill).

4.4 Knowledge Sharing

Knowledge can be shared through communication. In our knowledge-sharing model, two main factors, having a common goal (being in one group) and the desire to have connections with others (extraversion), can cause more knowledge sharing.

As mentioned in the *5th assumption*, Extraverted types are more likely to share their knowledge compared to Introverted types, who limit their social activities to a few people. So, the probability of sharing knowledge with another agent is related to two factors. IE_i (level of Extraversion of the agent) and In_i (in-group factor that is a binary value if agent j is in the same group, $In_j = 1$, or if an agent is in another group, $In_j = 0$). The probability of sharing knowledge is calculated as follows

$$Sh_{ij} = \frac{(\frac{w_{IE}EI_i}{100}) + w_{In}In_j}{w_{EI} + w_{In}} \tag{4.14}$$

Where Sh_{ij} is agent $i's$ probability of sharing knowledge with agent j. And weights w_{EI} and w_{In} indicate the importance of the Extraverted personality and the In-group factor, respectively. In order to have the same range for the both factors, Extraverted personality is divided by 100 in Formula 3.37. The willingness to accept shared knowledge is related to Knowledge-credibility (trust), and it is explained in the next section.

4.5 Trust (Knowledge Credibility)

Trust is a crucial part of knowledge sharing (Dignum & Eijk, 2005). The knowledge-sharing process entails two different socio-cognitive decisions (Castelfranchi, 2004):

1. A decision to pass or not pass on a piece of knowledge.
2. A decision to accept or reject a given piece of knowledge.

The degree of confidence that one has in the integrity and competence of the organizational environment is essential for both of these decisions (Dignum & Eijk, 2005).

Although trust can take different forms, we assume in our organizational context here that trust refers to the degree to which a person can have confidence in the information that he or she may receive from a coworker; and we call it knowledge-credibility. There are three principal routes by which we can acquire information relevant to team performance: team success, direct interaction, and indirect interaction:

1. ***Team Success***: This parameter reflects the history of previous team successes.
2. ***Direct Interaction***: agents gather information from the expertise of another agent who shares his knowledge.
3. ***Indirect Interaction:*** each agent gathers third parties' attitudes about other agents. The average of these attitudes determines the general reputation of the agent.

As a result, the overall Knowledge-credibility of agent i on agent j is calculated as follows:

$$Kc_{ij}(t) = \frac{(w_{Id}*Id_{ij}(t)+ w_{Re}*Re_{ij}(t)+ w_{Ts}*Ts_{ij}(t))}{(w_{Id}+ w_{Re}+ w_{Ts})} \tag{4.15}$$

Kc_{ij} refers to Knowledge-credibility of agent i to agent j at time t. This knowledge-credibility is affected by three factors: Ts_{ij} (team success), Id_{ij} (direct interaction), and Re_{ij} (indirect interaction or reputation). Weights w_{Id}, w_{Re} and $, w_{Ts}$ determine the importance of direct trust, indirect trust and team success, respectively. These three factors are explained in the following sections.

4.5.1 Team Success

Unlike traditional teams, in temporary teams people often have to work with people they don't know. This ability to quickly form a trusting relationship is called "swift trust" (Coppola et al., 2004). In reality this trust is not reliable and some other factors over time change the perception of people towards each other. Team success reflects agents' past team experiences with other agents and represents the total number of satisfying and successful group tasks.

If the performance of the task is less than the threshold, $\theta_1$the task is unsatisfying. Otherwise, it is satisfying. Agents update their belief about team members after each task by this formula:

$Ts_{ij}(t) =$

$$\begin{cases} Ts_{ij}(t-1) + e^{NS_i w_{NS}/100} * Pe_{ijb}/100 & if \ Pe_{ijb} > \theta_1 \\ Ts_{ij}(t-1) - \frac{e^{NS_i w_{NS}}}{100\,Pev_{ij}} & otherwise \end{cases} \quad (4.16)$$

$Ts_{ij}(t)$ indicates the belief of agent i about past experience with agent j. NS_i is the measure of the MBTI iNtuitive-Sensing scale, and here it is used to indicate the degree to which agent i is a Sensor. Pe_{ijb} represents the performance in task b, where agent i and agent j are team members. As mentioned above in the *2nd assumption,* for people with a Sensing personality, what happened in the past is a more important factor compared to iNtuition types, and w_{NS} indicates the importance of the Sensing personality on the team success factor for Knowledge-credibility.

4.5.2 Direct Interaction

Over the course of time, agents update their beliefs about other agents' expertise and develop their Knowledge-credibility. If agent j shares some knowledge with agent i, agent i develops his belief on (confidence in) the expertise of agent j as described in the following formula:

$$Id_{ji}(t) = \begin{cases} Id_{ji}(t-1) - \frac{w_{TF}(100 - TF_i)}{100} & when \ K_j = 0 \ and \ K_i = 1 \\ Id_{ji}(t-1) + w_{TF}(100 - TF_i)/100 & if \ Agent \ i \ accepts \ K_j \\ Id_{ji}(t-1) & otherwise \end{cases} \quad (4.17)$$

$Id_{ji}(t)$ indicates the direct trust of agent j on agent i; TF_i indicates the degree of Feeling personality of agent i; and $(100 - TF_i)$ determines the Thinking of this agent. And w_{TF} indicates the weight of Thinking-Feeling dimension. In this formula, we face three scenarios, which are based on the *1st Assumption* (above):

1. If agent j expresses his opinion about a topic on which he does not have any knowledge (i.e. $K_j = 0$), then it would have a negative effect on agent $i's$ opinion who knows that j is wrong. Agent i decreases his value of Knowledge-credibility based on his Thinking-Feeling personality. People with Thinking personality make judgements based on empirical verification, so it makes them more sensitive to false knowledge.

2. Agent i may accept the knowledge from agent j. The details about accepting knowledge are explained in the knowledge sharing section.
3. Agent i may receive knowledge from agent j and without knowing whether the knowledge is true or false. In this case it will not have any effect on agent j's Knowledge-credibility.

4.5.3 Indirect Trust (Reputation)

Agents not only compute Knowledge-credibility based on expertise and team success, but also, they collect recommendations from other agents. When agent l interacts with agent i and transfers his attitude towards a third party, agent j, he is building agent j's reputation for agent i. So the reputation of agent j is calculated as follows:

$$Re_{ij}(t) = Re_{ij}(t-1) + Kc_{il}(t) * Kc_{lj}(t) \quad (4.18)$$

$Re_{ij}(t)$ indicates the reputation of agent j for agent i at time t. $Kc_{il}(t)$ indicates the knowledge credibility of agent i to agent l, and $Kc_{lj}(t)$ indicates the knowledge credibility of agent l to agent j.

4.6 Knowledge Acceptance

As mentioned earlier, the willingness to accept shared knowledge is related to Knowledge-credibility (trust).This is relevant to Sensing personalities as mentioned in the *3rd assumption*. When agent i shares his knowledge with agent j, the probability that agent j accepts the knowledge is related to his Knowledge-credibility and Sensing personality. In the MBTI scheme, people with Sensing personalities are more willing to gather facts compared to iNtuition types. The probability that knowledge is accepted by agent j is calculated as follows:

$$a_{ji} = (w_{Kc} e^{Kc_{ji}}/10 + w_{NS2} NS_j/100)/(w_{KC} + w_{NS2}) \quad (4.19)$$

a_{ji} is agent j's willingness to accept knowledge from agent i that is related to two factors: Kc_{ji} (the Knowledge-credibility of agent j for agent i) and NS_j (the level of Sensing in agent j). Where weights w_{Kc} and w_{NS2} indicate the importance of Knowledge-credibility and the Sensing personality in accepting knowledge, respectively.

4.7 Self-Learning Knowledge

In addition to learning skill from others, we cover the effect of self-learning. In each time step, people increase their knowledge at a rate that is related to the Introverted and iNtuition components of their personalities. Introverted types have a higher self-learning rate than Extraverted types (*6th assumption*), and iNtuitive types can generate new knowledge by interpreting their past knowledge (*4th assumption*). This probability is calculated as follows:

$$Sl_i = \frac{\theta_{5*}(w_{IE2}(IE_i)/100 + w_{NS3}\ (1 - NS_i\ ))}{w_{EI2} + w_{NS3}} \tag{4.20}$$

The Sl_i indicates the probability of self-learning of agent i. Again, this probability determines the likelihood of a knowledge topic's value getting set to a value of 1. IE_i reflects where the agent lies along the Introverted-Extraverted personality dimension, and NS_i indicates where along the Sensing-iNtuition dimension (values are from 0 to 1). w_{IE2} and w_{NS3} indicate the importance of Introverted and iNtuition personality types, respectively, and θ_5 is the rate of self-learning knowledge growth.

4.8 Skill Learning

Employees not only learn the knowledge by interacting with other agents; they can also improve their skills or procedural knowledge by observing others' behavior. Observational learning is an effective method of collaborative learning that is commonly used by both human and computer models (Fernlund, 2004). In observational learning, people need a model to imitate the behavior. In our model, agents improve their skills by observing and imitating another agent who is using the same skill in their team. Two factors affect the improvement of skill – the difference between the skills of people who are performing the task and the amount of relevant knowledge that the learner has. In our simulation model, skill improvement of an agent is calculated as follows:

$$skill_{iv}(t) = skill_{iv}(t-1) + K_{evi}\theta_2\ (skill_{iv}(t-1) - skill_{-iv}(t-1)) \tag{4.21}$$

Skill improvement is affected by K_{evi} which represents the sum of knowledge related to $skill_{iv}$ and $skill_{iv}(t)$ indicates the skill v of agent i in time t, and θ_2 shows the growth rate of skill. $skill_{-iv}$ indicates the skill v of other members in the team, in other words it means the maximum skill of all the team members except agent i.

4.9 Forgetting

People forget their knowledge and skills if they stop using them, but the degree of forgetting differs in knowledge and skill. In order to model how people learn and forget knowledge and skill, we used declarative and procedural memory that is presented in the ACT-R cognitive architecture (Anderson, 2008). In this model, declarative knowledge represents factual information, and procedural knowledge indicates task knowledge.

In ACT-R, a declarative memory item is dependent on how often (frequency) and how recently (recency) the item is used. Also in the higher stages of learning, the strength of declarative memory increases by practicing. However, when knowledge is stored in procedural memory, it will not easily decay with time.

In our model, we assume that knowledge is stored in the declarative memory and skill is stored in the procedural memory. The forgetting rate in knowledge is faster than skill but also depends on the competency of agents in that skill. For example, once we learn swimming or riding a bike we never forget that skill, but there will be some decay in efficiency if we don't practice it. However, we might forget some facts we memorized in our childhood. So, skill deterioration (when employees are not using that skill) is calculated as follows:

$$skill_{iv}(t) = skill_{iv}(t-1) - \theta_3 e^{-(skill_{iv}(t))}\, skill_{iv}(t-1) \tag{4.22}$$

$skill_{iv}(t)$ indicates the skill v of agent i in time t, and θ_3 shows the forgetting rate of the skill.

In addition to frequency and recency, which are mentioned for skill forgetting, the competency in the skill related to that knowledge reduces the forgetting rate of knowledge (Kim et al., 2013).

Each time that a person uses knowledge; this knowledge is refreshed and is saved from forgetting. The probability that a person loses his knowledge is related to the strength of skill related to this knowledge. So, the probability of forgetting knowledge is calculated as follows:

$$P_{fk} = \theta_4\, e^{-(skill_{iv}(t))} \tag{4.23}$$

P_{fk}indicates the probability of forgetting knowledge, $skill_{iv}(t)$ indicates the competency in the skill related to knowledge, and θ_4 indicates the rate of knowledge forgetting.

4.10 Simulation

The proposed mathematical model was translated into an agent-based model and implemented in Repast Suite (North et al., 2007), an agent-based simulation environment. In this model, self-organizing teams perform a task in the context of a temporary project. Each temporary project consists of two tasks, and each task is related to a single skill, and two people are required to work on a task. So, a temporary project needs four employees.

The initial setup of the experiment comprised 40 employees and 10 tasks, with each task requiring four employees. Each individual has some initial properties, such as a vector of skills, a matrix of knowledge related to these skills, and a knowledge credibility vector of other employees. In each cycle, individuals team up and start a task. Each task takes 100 time-steps. In each time-step agents develop their trust of each other and knowledge that is explained in detail in Section 4.6 by communicating and updating their skills by observation. In this work, two task allocation mechanisms are studied: based on trust (knowledge credibility) and skill.

1) **Knowledge credibility:** In the first scenario, employees form a team based on their knowledge credibility. We assume one employee starts a task and asks three other members with the highest knowledge credibility to join that task.
2) **Skill competency**: In the second scenario, people are assigned to a task based on their skill competency. Managers assign a combination of employees with the highest skills as explained in Formula 4.7.

Initially, for each of the four personalities as measured by MBTI dimensions, we established a scale between 0 and 1 and assigned values for each employee. In our initial settings, a vector contains 10 knowledge items assigned to each skill. In addition to that knowledge, we have a general vector of knowledge that contains 100 elements. We assume each project needs a maximum of 50 elements of this knowledge.

The values assigned 1 for the all the weight parameter discussed and numbers 100, 0.1, 1, 10, 1 to the parameters $\theta_1 , \theta_2, \theta_3, \theta_4 and\ \theta_5$ respectively. We collected the results of 100 model runs for the model analysis. We ran two types of experiments. Firstly, we compared two task allocation mechanisms and their differences in knowledge learning, skill learning, and team performance by assigning *a random personality to the agents*. Then, we compared the effects of *different types of employees (in terms of personality)* and their roles in the team performances in two task allocation mechanisms. This is summarized in Figure 5.

```
Initialization: Group formation mechanism and inputs such as task
and team members' characteristics
For each task
 FOR time step < current-time step + 100 DO
  FOR each time step
   FOR each agent i
     With probability  Sh_ij Formula(4.14)
      Share knowledge with     agent  j
     IF receive a knowledge from agent j
      With probability of a_ij Formula (4.19)
      Accept the knowledge
      Update direct interaction Id_ji(t) Formula (4.17)
      END IF
     IF receive information about agent k
       Update Re_ik(t) Formula (4.18)
      END IF
       With probability  Sl_i Formula (4.20)
       Update knowledge
      When agent i using same skill as agent j
      AND they are in same team:
       Improve skill ΔSk_ij  Formula (4.22)
      WHEN agent i stops using skill v: forget
      WHEN agent i stops using knowledge  : forget Formula (4.23)
    END FOR
   END FOR
END WHILE
Calculate team performance Pe_b  Formula (4.13)
IF agent j is in the same team
Update team success trust Ts_ij(t)   Formula (3.16)
Next task allocation
```

Figure 5: Collaborative learning algorithm

In addition, this can be developed as a simulation tool to help managers and teachers identify how changes in knowledge, skill, and the performance of group members appear due to attributes such as personality, skill, knowledge, task requirements, and the task allocation mechanism.

4.11 Results

In our computer simulation, we compared knowledge growth, skill growth, and performance while performing 10 tasks (100 time steps for each of them that equals to 1000 time steps) using two task allocation mechanism. Figure 6 compares the average knowledge of employees (an average over 100 runs) for both team-formation mechanisms (based on knowledge credibility and skill). Figure 7 shows a comparison of the average skills of employees (averages over 100 model runs) for both team-formation mechanisms – based on knowledge credibility and skill-based team formation after 10 tasks (1000 time steps). Figure 8 compares the average team performances (averaged over 100 model runs) for both team formation mechanisms based on credibility and skill-based team-formation after 10 tasks.

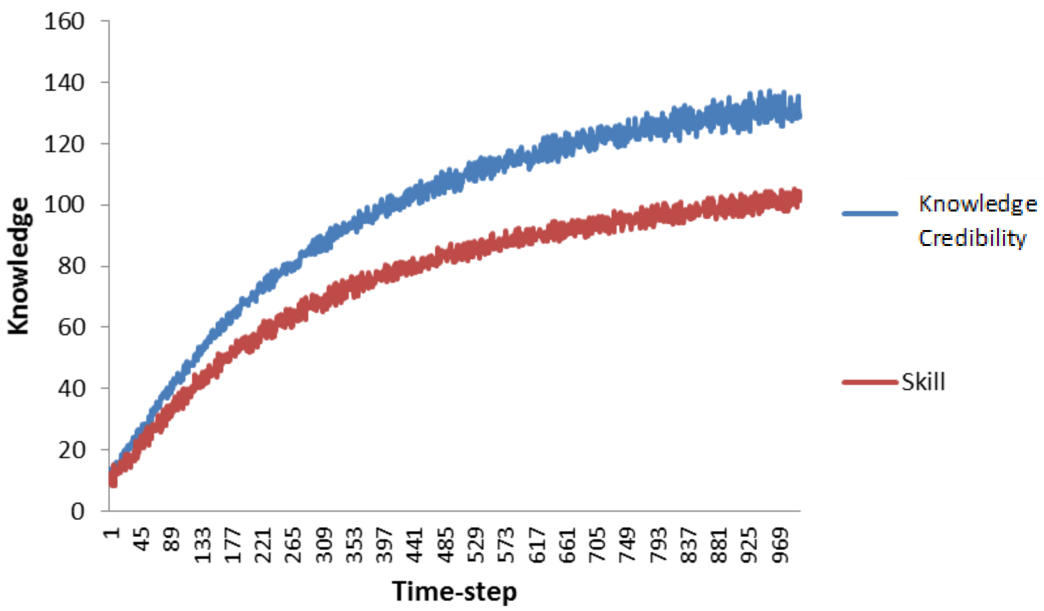

Figure 6: Knowledge growth for credibility-based teams and skill-based teams.

The simulation results showed the average performance of teams in skill mechanisms had better performance compared to the credibility mechanism (see Figure 8). However, the gap between the two results shrank over time. Despite this gap in the performance, the average knowledge in teams based on knowledge credibility is much higher than teams based on skill (see Figure 6). Skill growth in teams with the skill-based formation is faster than the credibility-based team formation scenario (see Figure 7); however, the results show that the average skill growth has a lower growth rate over the long term.

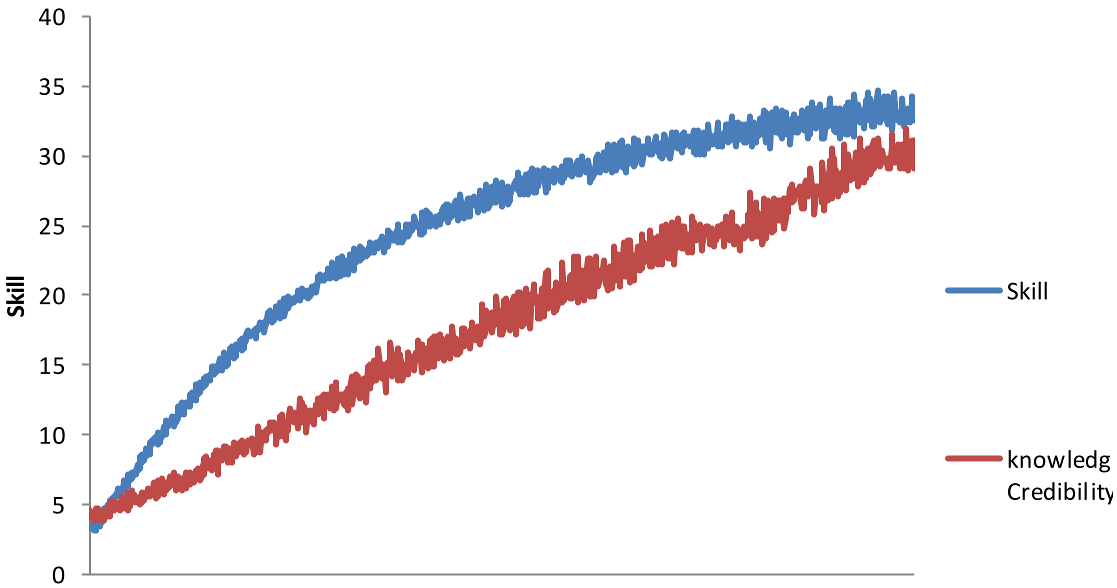

Figure 7: Skill growth for knowledge credibility-based teams and skill-based.

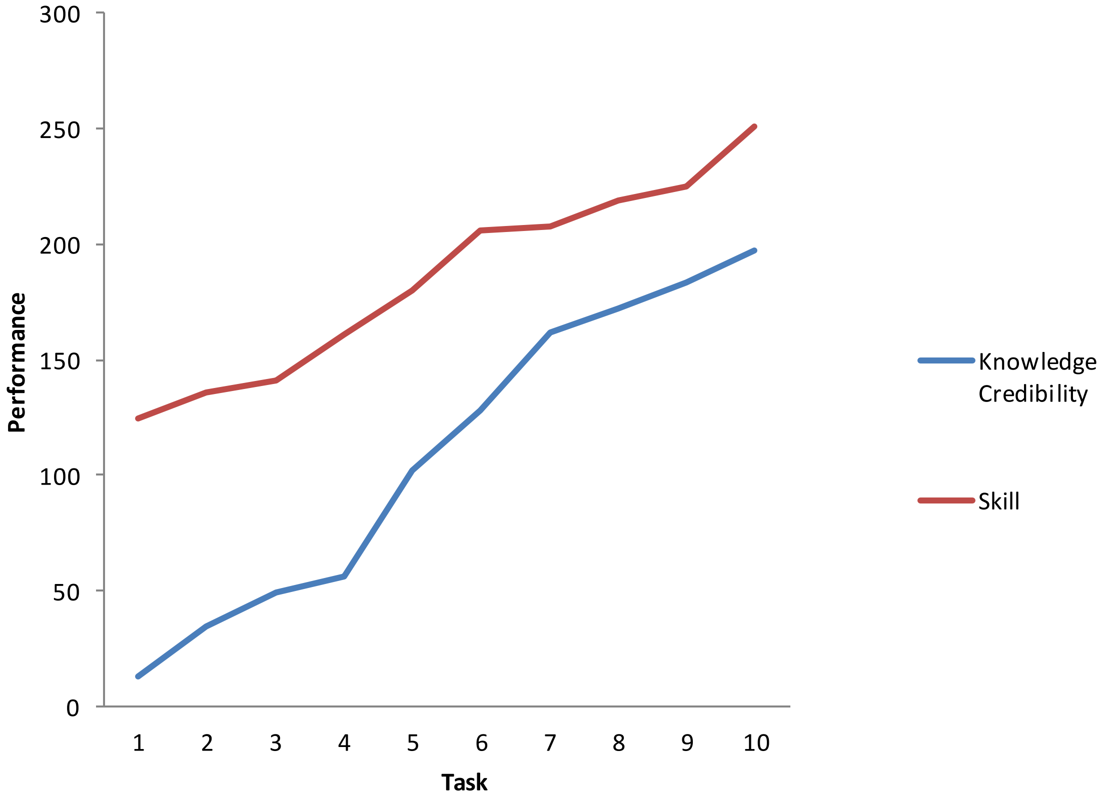

Figure 8: Performance for knowledge credibility-based teams and skill-based teams.

In addition, we analyzed the effects of personality on team performance and the differences of these effects on the two task allocation mechanisms. In this connection, we conducted new simulations and instead of assigning random values to personality, specific personality values assigned to all employees for a team. We conducted experiments over two scenarios with different personality value settings and measured the average performance after performing 10 tasks. These scenarios were measured for two self-assembly mechanisms (based on skill and based on knowledge credibility) and are shown in Figure 9, which shows a heat map of performance, with each value of a matrix representing a different color (with a low value represented by red and a high value represented by white). Rows represent the dimensions of personality, and the columns represent the value of each dimension. These results represent the performance values of different configurations (6 configurations given in the y-axis). For example, the first row from the bottom (I-E-C) shows a particular distribution of Introverted-Extraverted (I-E) personality with respect to the Knowledge-credibility mechanism (C). The number 0.1 in the Personality axis indicates that 0.1 is assigned to the I_E personality dimension of all the agents. In this scenario, the average performance of teams in 10 tasks is equal to 10. The second row from the bottom (I-E-S) shows the Introverted-Extraverted (I-E) personality with respect to the skill mechanism (S) and the first number is a scenario for which the number 0.1 assigned to that particular personality trait of the employees, and the average performance was 8. By comparing these two values, we observe the difference between team performances based on team formation mechanisms (represented by C (knowledge credibility mechanism) and S (Skill –based mechanism) at the end of the triples shown on y-axis).

The results reveal that there is a relationship between personalities of employees and the overall performance. Results show Extraverts have a positive effect on performance for both team assembly mechanisms based on trust and skills (see the right hand side of the last two rows of results in Figure 3.10). However, a balance of Introverts and Extraverts led to a better result compared to the scenarios for which all members are very Extraverted. The observed behavior showed increasing Extraversion had a positive effect in the Skill-based scenarios (5^{th} row of results) compared to the Knowledge-credibility-based scenarios (6^{th} row of results). In other words, if team members are skillful, some teams' members with a particular personality (such as being Extraverted) could end up with more knowledge-sharing and consequently improved performance.

Sensing-iNtuition personalities have almost opposite effects on the two team-formation mechanisms, and they follow different patterns. Intuition is a more important factor in Knowledge-credibility-based (3^{rd} row of results) teams compared to skill-based teams (4^{th} row of results). A simple, approximate explanation of this behavior is as follows. First, in a system where all the employees are Sensors, they are eager to gather additional knowledge. Since teams are formed based on knowledge credibility, this virtue assists them for a high knowledge-sharing rate. When team formation is based on skill and employees are iNtuitive, they do not share their knowledge as much as team formation based on knowledge credibility mechanism and this phenomenon results in negative learning and consequently poor performance. It must be noted that in each of these simulations, all of the agents have similar personalities and the TPD is zero. Although, having similar personalities is not realistic, comparing these scenarios provides insight about the impact of personality and team formation mechanism on each other.

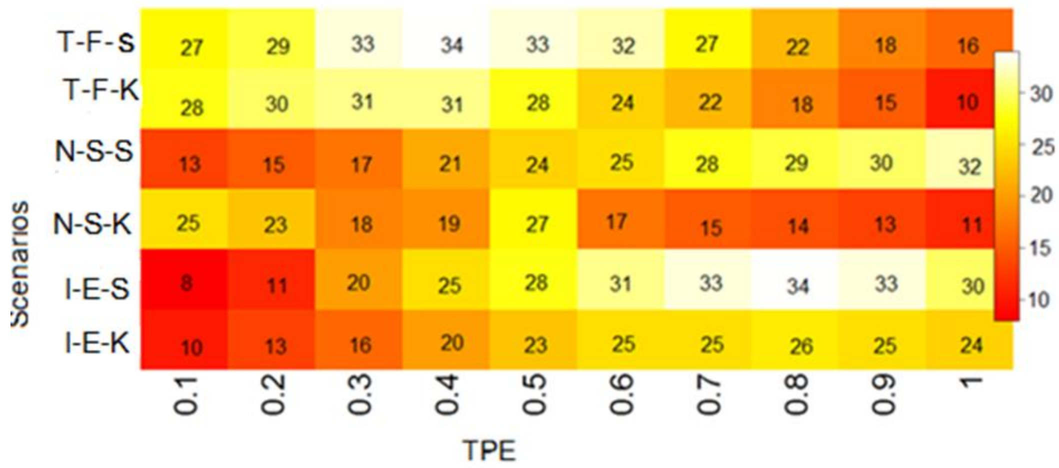

Figure 9: Performance and personality in credibility-based teams and skill-based teams

Having a high Thinking personality was shown to be better in our simulations than having a high Feeling type of personality in most of the cases. The Thinking personality had better success on team formation (see row 2, first half of the results) based on knowledge credibility compared to team formation based on skill (row 1, first half of the results). This reflected the effect that when people have Thinking personalities and team formation is based on knowledge credibility, they eventually find better teams to work with. When people are Feelers, they might trust the wrong persons and give them the credit that they do not deserve; however, in a world with Thinking people these mistakes less likely occur.

4.12 Conclusion

In this chapter, we investigated how the team formation mechanism affects collaborative learning, and consequently team performance, of self-assembly teams. To do that, a modifiable template was developed for the examination of dynamic knowledge and skill influences on individual and team performance via simulation experiments. During the simulations, agents exchanged their knowledge with teammates and updated their trust concerning the knowledge of other agents. Also, they improved their skills by observing and imitating their teammates' behaviours.

Two team formation mechanisms were compared: one based on trust (knowledge credibility) and one based on skill. In the first scenario, employees formed a team based on their trust or knowledge credibility towards other agents. In the second scenario, agents were assigned to a task based on their skill competency.

The simulation results showed that the gap between the two results shrank over time, and that overall, the average performance of teams formed based on skill mechanisms outperformed the average performance of teams formed based on the knowledge credibility mechanism. In contrast, the average knowledge in the teams which were based on knowledge credibility was higher than that knowledge of the teams based on skill. Moreover, it was observed that the skill growth in teams with the skill-based formation was faster than the skill growth in the knowledge credibility-based team formation scenario.

CHAPTER 5

5 TEAM FORMATION MODEL AND GAME ENVIRONMENT

In Chapter 3 and Chapter 4 we developed two models to demonstrate the team formation effect on team performance. In these models, the team members did not have full autonomy for selecting a team member and also team selections were not only dependent on personality since the skill and knowledge of team members were highly involved. In order to analyse the effect of team formation mechanism on team performance and vice versa, we choose serious games (the games with a purpose other than entertainment) in which players do not need competence in a skill and they do not have any obligation for selecting a team member.

In this chapter, we develop a model in games in which the personality determines the strategy of agents in team formation. Virtual worlds and game environments provide a platform for analysing team activities in terms of their performance and composition (Reeves et al., 2007). As games serve as a platform for analysing the behaviour of the team assembling and team behaviour and the model has the potential to be validated by some real data by other researchers, serious games were selected. We designed a simulation model based on a serious game with the purpose of promoting sustainability.

In this model, we investigate the effects that player personality can have on team performance in games that have been designed to have a social purpose ("serious games"), such as games intended to enhance more consideration for the environment and for sustainable energy usage. The work involves multi-agent-based models of team play and, fuzzy-logic-based MBTI parameterization of player personality. Experiments employing agent-based simulation are then presented that show *the effects of various combinations of personality and temperament types on team performance in the context of competing team profiles*. The results from this model are published in Farhangian et al., 2013.

Although some of the most popular games are those in which a single user tries to achieve a high score by playing against a machine, team-oriented games are more naturally suited to induce the desired collaborative and cooperative attitudes necessary for improved “green” behaviour (some of these behaviours are presented in Table 5.2). However, team games are more difficult to design so that they have the appropriate compelling gameplay and cannot be dominated by a single player. In this respect, one does not want a game that is dependent on the skill of the most talented player – rather, one wants a game that is likely to be won by the team that employs the most teamwork. So the individual game activities in this kind of game should not be particularly difficult or demanding. What should matter is the teamwork.

To assist the team-oriented game designer, we have constructed an agent-based model of a “serious game” in order to examine how personalities of players affect their team selection strategies and consequently the game performance. In the work presented here, we are particularly interested in the issue of teamwork and how the different player “personalities” can affect team composition and team performance in the game. Unlike the two other models presented in Chapter 3 and Chapter 4, team formation in the games is entirely self-assembly.

In our agent-based game design, in addition to MBTI, we employed Temperament theory (Keirsey 1998) that is related to the MBTI scheme, indeed a pared-down version of it. Temperaments can be considered to be aggregations of MBTI types into smaller groups. Keirsey describes:

- SJ group as “The Guardians” or “Security Seekers” or Duty Seekers which consists of ESTJ - "The Supervisors", ISTJ - "The Inspectors", ESFJ - "The Providers" and ISFJ - "The Protectors".
- SP group as "The Artisans" or “Sensation Seeking" or “Action Seeker” which consists of ESTP - "The Promoters", ISTP - "The Crafters", ESFP - "The Performers" and ISFP - "The Composers".
- NT group is described as "The Rationales" or “Knowledge Seekers” and includes: ENTJ - "The Fieldmarshals", INTJ - "The Masterminds", ENTP - "The Inventors" and INTP - "The Architects".
- NF group is described "The Idealists" or “Identity Seeker” or “Ideal Seeker” and includes ENFJ - "The Teachers", INFJ - "The Counselors", ENFP - "The Champions" and INFP - "The Healers".

These groups are summarized in Table 5.1.

Table 5.1: Temperaments and their mappings to MBTI types

Temperament	MBTI Types
Duty seeker	ESFJ, ISFJ, ESTJ, ISTJ (SJ)
Knowledge seeker	ENTP, INTP, ENTJ, INTJ (NT)
Action seeker	ESFP, ISFP, ESTP, ISTP (SP)
Ideal seeker	ENFP, INFP, ENFJ, INFJ (NF)

5.1 Structure of Environment and Serious Games

Serious games that educate and motivate people to have greener educational awareness and consciousness is an area of interest for both researchers and practitioners (Michael et al, 2005). Through playing a game, players can create an inspiring environment for environmental sustainability. Serious game technology in this domain takes advantage of the effect of team members on each other and their cooperation on the issues such as energy consumption reduction, the use of renewable energy, and employing sustainable development approaches.

In order to gain a better understanding on team behaviour in an environment that team members have autonomy to make up a team, we developed an agent-based model in which players team up primarily for entertainment and through playing they also undertake some environmental friendly tasks. Teams are scored by a task that is submitted and evaluated by their peers.

In this model, we constructed a game involving four-member teams that would engage in various tasks involving environment-enhancing activities. Teams would draw mission "cards" that stipulated the tasks to be performed, and then the team would have to go out and perform the tasks. All the tasks require group cooperation. The basic sequence of gameplay is shown as a flowchart in Figure 10 that includes the four following major steps:

1. Agents look for mission assignment cards in their neighborhood.
2. When an agent finds a task, it invites other teammates to join it.
3. If the minimum number of teammates is not achieved (i.e. two), then the recruiting agent waits for a short time and repeats its request.
4. After the agents start a task, we use personality composition measurements to see how they perform during the task.

In our game environment, we considered two types of tasks:

- ***Structured tasks:*** these are not complex. These tasks require individual team members to use less cognitive resources, and they have specific question and specific answers.
- ***Open-ended:*** or ‘cognitive’, tasks that require relatively more creativity and imagination.

Some examples of open-ended and structured tasks are shown in Table 5.2.

Table 5-2: Tasks on mission cards

Open-ended task	Structured task
Host and participate in an event for lunch and have a short tutorial about healthier food	Check different kinds of bins (paper, compost, plastic and trash bins) and make sure waste goes to proper bins. Teams can compete together and gather as much waste as they can gather in bins
Present survey results about sustainability issues	Fill assessment sheets to assess sustainability in different parts of the town
Start a recycling program	Tree-planting event
Express sustainability issues through arts and crafts	Teams put out some bins in the city for second-hand clothes or other sharing items
Film current sustainable projects and activities and upload to Internet	Offering waste reduction tips for consumers
Run an event for swapping second hand clothes	Gathering donations for non-profit green organizations

The effectiveness of a team's performance in these types of projects or games can be strongly influenced by the personality makeup of the team (Contractor, 2013). In our work, we have developed a model that shows how personality as measured by MBTI can be used for agent-based modelling of teams. Moreover, the modelling approach outlined in this research can be of use for policy makers whose aim either is fostering sustainability via behaviour change or is simply discovering what is the most effective team composition. The model can also be used to recruit team members of certain personalities in order to perform certain type of tasks.

Figure 10 illustrates how our game works. This is from one agent's point of view and describes how it starts a task or forms a group and performs the tasks during the game.

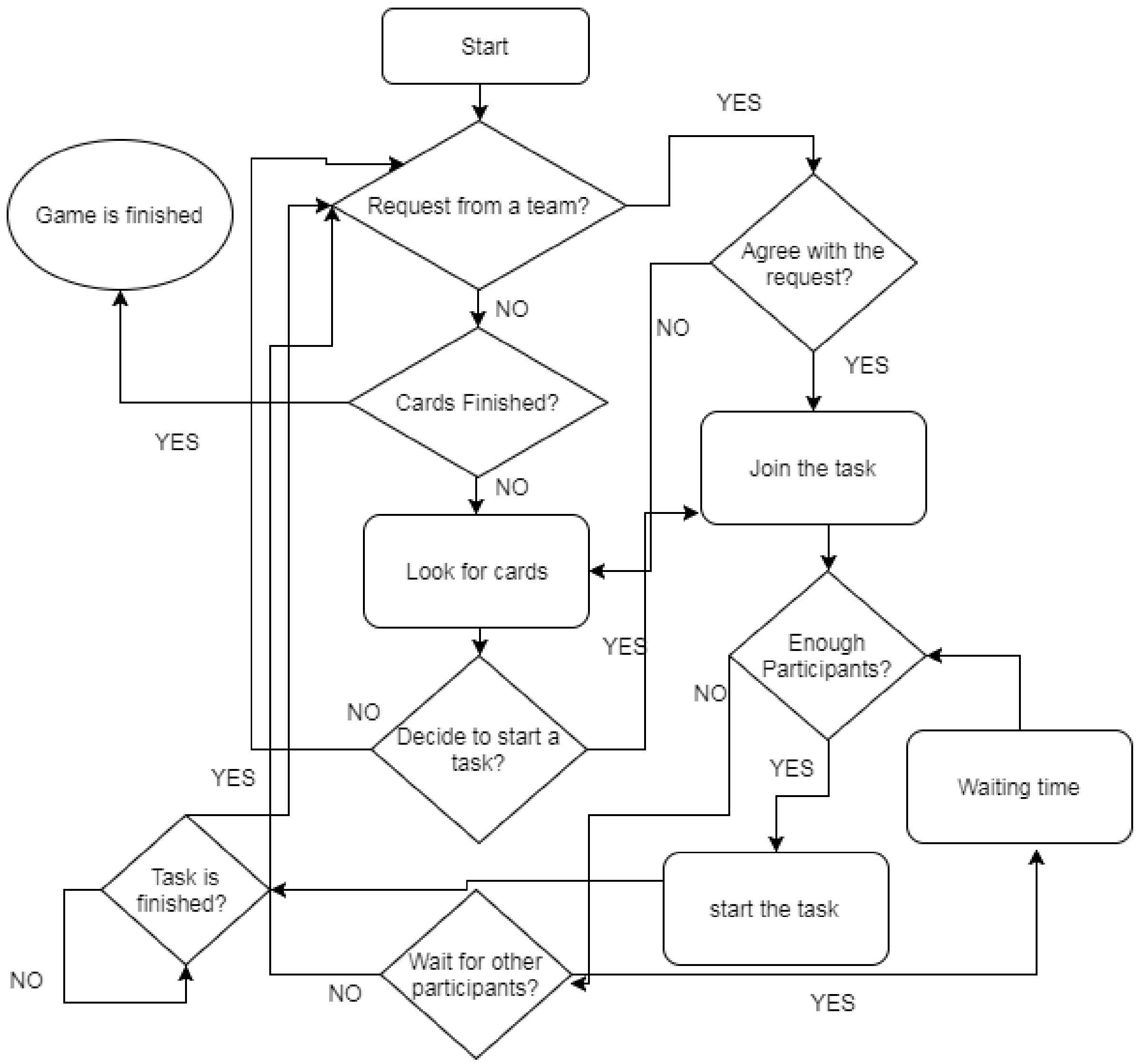

Figure 10: Game flowchart

In the next section, we show how personality types, as indicated by MBTI measures, can collectively affect team performance.

5.2 Personality and Team Behaviour

Personalities of players determine their behaviour, such as team assembly and team performance through the game. The effect of personality as measured by MBTI is described as follows:

Personality and gathering information: Intuitive people (MBTI: N, as opposed to S) focus on the big picture and look for overall patterns, rather than focussing on details. They are looking for something larger than just the current activities. In contrast, Sensing people (S) prefer to collect all the immediate information around them. So they spend more time tracking than doing (Myers et al. 1985). Therefore, we assume that in games, iNtuitive (N) people are faster overall in making up their minds for doing a new task than Sensing people (S), who may need more time to know all the information about that task.

Personality and Interaction: In connection with thinking and feeling (the T-F dimension of MBTI), Feeling people are more likely to be concerned about the impacts of their decisions in connection with their social context. Thinkers follow their objective principles and standards that are less influenced by context (Myers et al. 1985). Therefore, T-people are logical, and F-people make decisions based on their heartfelt concerns.

Moreover, when it comes to joining up to make a team, the sociability level of a person can be a factor. This is the I-E (Introversion vs. Extraversion) dimension of MBTI. Extraverts are energized by interacting with others, and so they prefer to work in groups. Introverts prefer to work alone to get things done. As a result, we assume having a high Feeling and Extraverted personality has a positive effect on a player's decision to interact with others. These factors affect players' behaviour for asking others to join them and also replying to others' requests to join in the task.

Personality and flexibility: After players decide to start a task, they send requests to others to join them. In this stage, the Judging vs. Perceiving aspect of one's personality (the J-P dimension of the MBTI scheme) comes into play. Judgers (J-people) prefer to operate in a planned and settled fashion, while Perceivers (P-people) can operate in a more flexible and spontaneous way – they prefer to remain open to new information that may come in at any time (Myers et al., 1985). Therefore we assume Judging types are more likely to wait longer for others to join them, whereas Perceiving-people may leave a task in order to opportunistically pursue a new task.

5.3 Personality and Team Performance

As we discussed earlier, during task activities, a team's personality composition strongly influences success in finishing a task. To model this aspect of team performance, we investigated the degree to which differing personalities can work together effectively as a team. In this connection, we examined (a) single team metrics that quantify certain aspects of team composition as well as (b) a more detailed examination of team composition.

Similar to our model for computation of performance and personality, the following rules are merely applicable for this example. There are no global rules for the relationship between personality and team performance, and several factors should be addressed such as task structure, organization's structure, and organizational culture. In Chapter 8, we will argue for a data-driven approach needed to determine these rules that are specific for each organization. Considering the studies in the literature and the circumstances of our example, we have created the following rules.

With respect to TPE that was introduced in the section 2.4, we have made the following assumptions.

- A high TPE in Sensing (S) is presumed to have a positive effect on structured tasks. Recall that MBTI Sensing and iNtuition concern how people gather information. Sensing people are fact-driven and prefer to develop a single idea fully. As a result, when the task is structured and considering the detail is a key point in improving the task quality, a group of Sensors have a more positive effect on the task compared to a group of iNtuitive types.
- A high TPE in Judging (J) is also taken to have a positive effect on structured tasks. People high in Judging prefer to live according to plan and avoid extended periods of doubt. Some researchers have confirmed the positive relationship between conscientiousness and team performance for pooled tasks (Driskell et al., 1987).
- A high TPE in iNtuition (N), however, has a positive effect on open-ended tasks. iNtuitive people are imaginative and creative. They tend to think about several things at the same time and make connections between them.
- A high TPE in Feeling (F) has a positive effect on both open-ended and structured tasks. Feeling can lead to greater cohesion among team members. Some research has shown that 'agreeableness' from the Five Factor Model, which is correlated with Feeling in the MBTI model, has a positive effect on team performance (Driskell et al., 2006). In the connection with 'green' activity, Feeling is expected to

play a significant role, because green actions support the activities of others; and F-people try to meet the needs of others, even at the expense of their own needs.

- A high TPE in Thinking (T) can have a positive effect on structured tasks. Thinkers follow rationally-derived procedures, which conform well to structured tasks.
- With respect to TPD that is introduced in the section 2.4, we make some further observations.
- A high TPD in the Judgmental-Perceiving (J-P) domain has a positive effect on open-ended tasks. A Perceiver is flexible and often finds new ways to do things, but at the same time they sometimes dwell on the task work at the expense of reaching closure (Bradley & Hebert, 1997). Overemphasis on Judgment in complex tasks might lead to premature completion of the project with limited achievement; while overemphasis on Perceiving might lead to interim successes without final task completion. Therefore, it might be good to have a team with a mixture of Judgers and Perceivers.
- A low TPD in the Sensing and iNtuition (S-N) domain can have a positive effect on structured tasks. The literature suggests that homogeneity in this area tends to benefit teams in connection with tasks that are well-defined (Bowers et al., 2000). Homogeneity in this area can have two main beneficial consequences: integration and conflict avoidance (Bowers et al., 2000). This is because highly iNtuitive (high N) people are self-directed and know what they want, which can make Sensing people (high S) frustrated.
- A high TPD along the Sensing-iNtuition (S-N) axis is believed to have a positive effect on open-ended tasks. Having a balance in this connection can be advantageous, because people with high iNtuition can see the big picture, and the ones with high Sensing can then put the derived concept into action (Mansoor & Ali, 2013).
- A low TPD along the Feeling-Thinking (F-T) axis is expected to have a positive effect on both open-ended and structured task performance. A disparity on a team with respect to Feeling and Thinking can conflict with the decision-making process. In that case, some of the team members are concerned with the longer-term impacts of their decisions, while others focus on the immediate pros and cons of the decisions. Research with respect to the Five Factor Model category of

‘agreeableness’, which is thought to correspond to the Feeling type of MBTI, suggests that homogeneity with respect to agreeableness has a positive effect on team performance (Mohammed & Angell, 2003).

- A high TPD along the Extraverted-Introverted axis (E-I) is expected to have a positive effect on both structured and open-ended tasks. Extraverts increase team communication, but too many of them may be deleterious and lead to a decreased focus on getting the job done (Neuman et al., 1999).

The rules for team performance are based on assumptions that were described earlier. These rules are only assumed based on our proposed environment and can be different in other environments. Accordingly, some factors affect performance of structured tasks (we abbreviate the given effect by using the numbered letters shown in parentheses) -- such as TPE in Sensing (S1), TPE in Judging (S2), TPE in Feeling (S3), TPE in Thinking (S4), TPD in Sensing and iNtuition (S5), TPD in Feeling and Thinking (S6), and TPD in Extraverted and Introverted (S7). Factors affecting performance in open-ended tasks included TPE in iNtuition (O1), TPE in Feeling (O2), TPD in Judging and Perceiving (O3), TPD in Sensing and iNtuition (O4), TPD in Feeling and Thinking (O5), and TPD in the Extraverted and Introverted category (O6). These factors are crucial for agents to estimate the probability of performing the task successfully in each attempt.

Rules were then constructed for structured tasks and open-ended tasks and are presented in Appendix A. Such fuzzy rules are executed for each team to show their performance in structured and open-ended tasks. The encoded fuzzy model is described in the next section.

5.4 Fuzzy Model

Fuzzy set theory (Zadeh, 1965) offers a way of representing vagueness in the daily life. In social simulation, fuzzy logic is widely used to deal with the uncertainty and subjectivity in human society (Izquierdo et al., 2015). Because we are constructing an agent model of players who make decisions with respect to imprecisely-known information, the agents employ a fuzzy-reasoning decision model. In this respect, the agents deal with information that can have a fuzzy membership value with respect to their categorization. Thus, for example, considering size, something could be considered to be both medium-sized (to a certain degree by having a fuzzy membership value between 0 and 1) and large (also with a fuzzy membership value between 0 and 1). Some examples are provided in this section.

The fuzzy logic we employ is based on Takagi-Sugeno-Kang (TSK) fuzzy inferencing (Takagi & Sugeno, 1985), which is similar to Mamdani fuzzy inferencing (Mamdani, 1974) but has advantages with respect to computational efficiency. The general form of TSK method which is employed in this work presented as follows:

IF x_1 is $A_{1,r}$ and … and x_p is $A_{p,r}$ **THEN** $y_r = f_r(x_1, x_2, \dots x_p)$ (5.1)

Where

$A_{p,r}$ is a partitioned domain of the input variable x_p in the $r-th$ If-Then rule,

p is the number of input variables, and

y_r is the output variable in the r_{th} If-Then rule.

It is assumed that there are R_r $(r = 1,2, \dots, n)$ rules, and for each implication of R_r .we have

$$y_r = f_r\left(x_1, x_2, \dots \dots x_p\right) = b_{0,r} + b_{1,r}x_1 + \cdots, b_{p,r}x_p \tag{5.2}$$

Where $b_{0,r}, \dots, b_{p,r}$ are consequents of the input variables that specify the variables involved in the r_{th} rule's premise.

The weight of input variables is calculated as follows:

$$r_r = T\ (\mu_{A_{1,r}}(x_1), \dots, \mu_{A_{p,r}}(x_p)) \tag{5.3}$$

Where T is the minimum *t-norm* which is recommended by Mamdani and called the Godel t-norm that can be presented as the following:

$$r_r = \min\{\ \mu_{A_{1,r}}(x_1), \dots, \mu_{A_{p,r}}(x_p)\ \} \tag{5.4}$$

The final output y inferred from n implications is given as the average of all the weights r_r:

$$y = \frac{\sum_{r=1}^{n} r_r \times y_r}{\sum_{r=1}^{n} r_r} \tag{5.5}$$

To illustrate, in one stage of task activity, agents must decide to start a task or not, which will depend on the degree of Extraversion and Feeling in the personality. Here the input is the degree of one's Extraversion and Feeling, and the output is the level of confidence about starting a new task, which can be "High interested", "Medium interested" and "not interested". The membership function of Feeling and Extraverted behaviour is illustrated in Figures 5.2 and 5.3. The sets related to the linguistic variable "Feeling" and "Extraverted" are those representing membership grades to fuzzy sets shown in Table 5.3.

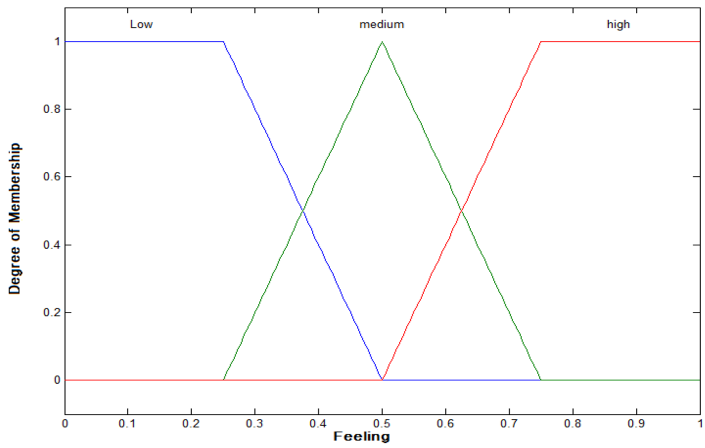

Figure 9: Membership functions of feelers

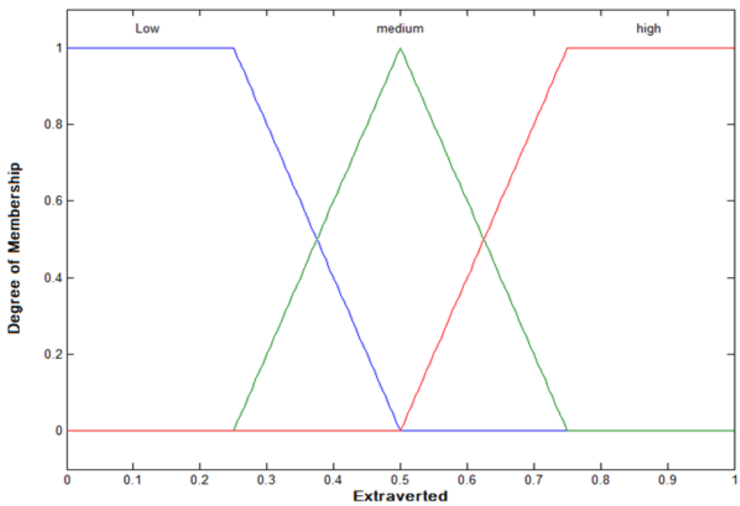

Figure 12: Membership function of Extraverts

Table 5.3: Membership grades

The characteristic functions of the sets reacted to linguistic variable *Feeling and Extraverted* are :
$$\mu_{feeling-low}(x) = \begin{cases} 0 & x > 50 \\ \dfrac{50-x}{50-25} & 25 \le x \le 50 \\ 1 & x < 25 \end{cases}$$
$$\mu_{feeling-medium}(x) = \begin{cases} 0 & x \le 25 \\ \dfrac{x-25}{50-25} & 25 < x \le 50 \\ \dfrac{75-x}{75-50} & 50 < x < 75 \\ 0 & \mathrm{x} \ge 75 \end{cases}$$
$$\mu_{feeling-high}(x) = \begin{cases} 0 & x < 50 \\ \dfrac{x-50}{75-50} & 50 \le x \le 75 \\ 1 & \mathrm{x} > 75 \end{cases}$$

The nine fuzzy rules for this activity are shown in Table 5.4:

Table 5.4: Fuzzy rules about interaction

IF	*Feeling*	AND	*Extraverted*	THEN	*Interaction*
R1	High		High		High Interested
R2	High		Medium		High Interested
R3	High		Low		Medium Interested
R4	Medium		High		High Interested
R5	Medium		Medium		Medium Interested
R6	Medium		Low		Not Interested
R7	Low		High		Medium Interested
R8	Low		Medium		Not Interested
R9	Low		Low		Not Interested

By using linguistic rules, a knowledge base was constructed for analysing these linguistic variables. The linguistic rules for this example are presented in Table 5.4. For example, we assume crisp input data for Feeling and Extraverted. Let us consider $\text{Feeling} = 70$ and $\text{Extraversion} = 45$. According to Table 5.4, then the feeling is considered to be *medium* with a degree$\mu_{feeling-medium}\,(70) = 0.2$; and it is considered to be *high* with a degree$\mu_{feeling-high}(x) = 0.8$. Extraversion is considered to be *low* with $\mu_{extraverted-low}(45) = 0.2$, and it is considered to be *medium* with $\mu_{extraverted-medium}(45) = 0.8$.

Four activated rules for these sets can be found in Table 5.4: R2, R3, R5, R6. We employ the zero-order TSK method, where the output of each fuzzy rule is constant, and all consequent membership functions are represented by a singleton spike. In this case, each output is a constant number representing an agent's interest to start a task.

"High interested" = 75 =k_1 ; "Medium interested" = 50 = k_2 ; "not interested" = 10 = k_3

And by using formula (5.4):

$$r_2 = \min\{\mu_{feeling-high}(x), \mu_{extroverted-medium}(45)\} = 0.4 \qquad (5.6)$$

$$r_3 = \min\{\mu_{feeling-high}(x), \mu_{extroverted-low}(45)\} = 0.2 \qquad (5.7)$$

$$r_5 = \min\{\mu_{feeling-medium}(x), \mu_{extroverted-medium}(45)\} = 0.6 \qquad (5.8)$$

$$r_6 = \min\{\mu_{feeling-medium}(x), \mu_{extroverted-low}(45)\} = 0.4 \qquad (5.9)$$

And by using Formula 5.5

$$Z = \frac{r_2\,k_1 + r_3\,k_2 + r_5\,k_2 + r_6\,k_3}{r_2 + r_3 + r_5 + r_6} = 62.5 \qquad (5.10)$$

The value of Z denotes the probability of an agent starting a new task (i.e 0.625 in this case). This process is illustrated in Figures 13 and 14. Figure 13 illustrates the max-min inference and the Mamdani inference that includes a representation of the fuzzy sets involved in the definition of the rules. The surface viewer in Figure 14 demonstrates the dependency of variables (i.e. Extraverted, Feeling and Interaction) to each other and we can see how they are affected by each other.

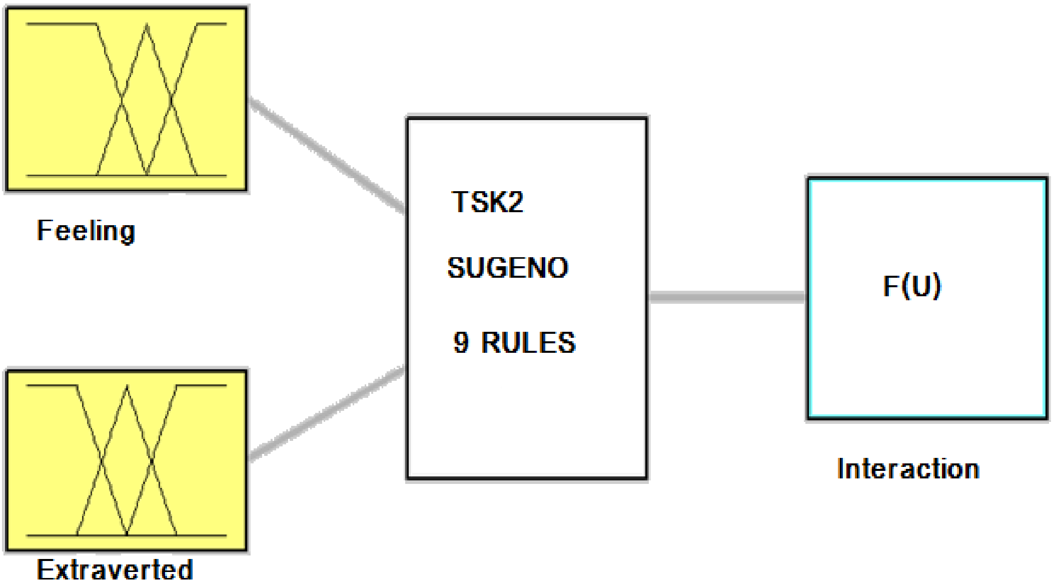

Figure 10: Fuzzy inference system and the probability of interaction with teammates

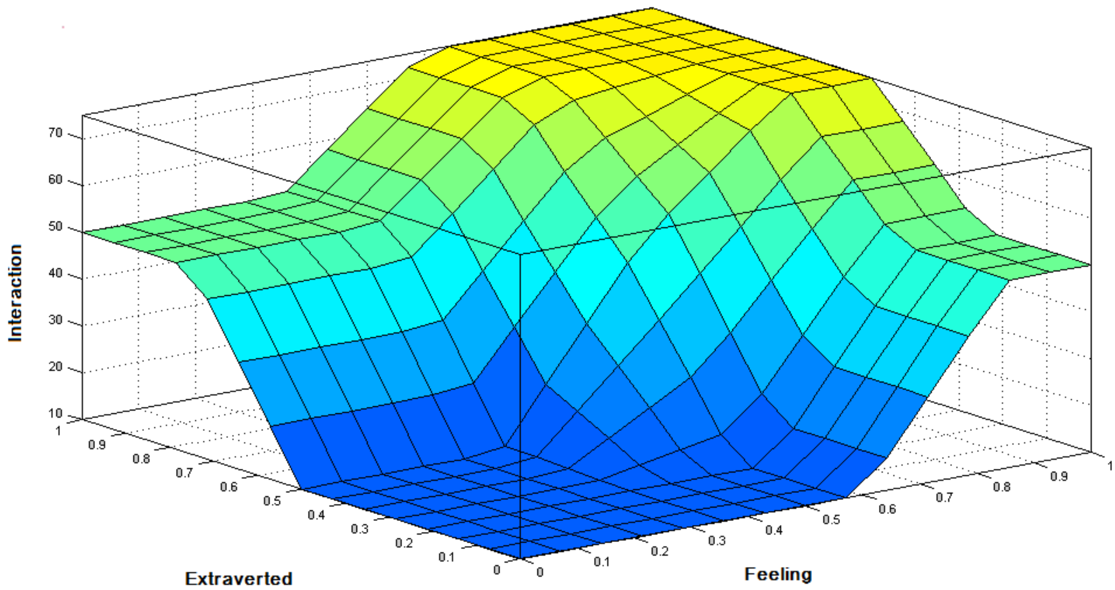

Figure 11: Fuzzy surfaces for Feeling, Extraverted, and Interaction

5.5 Experiments

We then conducted agent-based simulations with teams assigned to complete green-oriented tasks. Four teams compete against each other to find and finish the tasks. Teams received a score based on the tasks that they completed. The following algorithmic steps for agent behavior involving the use of fuzzy rules were then employed:

1. Stochastic values for personality were assigned to each agent. The values are then used to assign fuzzy membership.
2. Agents look for mission assignment cards in their neighborhood.
3. Agents find the card. If they are *Sensors*, they wait for a few seconds to know all the information about the tasks; otherwise they are *iNtuition* agents that make up their minds very fast.
4. Agents make their decisions whether to start the task. The alacrity of this decision is influenced by the degree to which they have a *Feeling* and an *Extraverted* personality.
5. When an agent finds a task, it invites other teammates to join it. At least two agents are needed for starting a task. (Again, they accept or decline a request according to their (fuzzified) interests in starting a task as determined by their Feeling/Thinking and Extraverted/Introverted personalities). The score depends on the number of agents in a team. If four members of a team do a task successfully, they score a value of one. In the cases that fewer agents finish a task successfully, the scores for two and three agent teams are 0.5 and 0.75, respectively.
6. If the minimum number of teammates is not achieved (i.e. two), then the recruiting agent waits for a short time and repeats its request. The duration that they wait for others is limited and depends on its *Judging/Perceiving* personality - Judgers wait longer and Perceivers, who prefer to keep their options open, wait less.
7. After the agents start a task, we use personality composition measurements to see how they perform during the task. The *TPE* and *TPD* values of the group members who are working on a task are computed. Recall that TPE is the mean of each personality and TPD is the standard deviation of each personality. After

fuzzification and applying the rules, the performances of teams are determined. Defuzzification (Formula 5.5) determines the probability of finishing the tasks.

5.6 Results

The simulation study examined all 3876 (all the possible combinations of four personalities among 16 personalities for four team members) MBTI team combinations in a four-team competition. With respect to the results and the computed scores, we note the following:

- An individual experimental run involved teams whose members had randomly selected MBTI personalities working on the completion of 200 tasks (100 open-ended and 100 structured), which usually took about 10,000 time steps. These runs were repeated 3876 times with different randomly selected team-personality makeups in order to ensure that all possible personality combinations occurred. The score for each team combination was calculated based on the average number of tasks that that team completed successfully.
- All the 3876 possible combinations are ranked for structured and open-ended tasks based on their average scores.
- The aggregated average performance for each individual personality in the overall team scores is shown in Tables 5.5 and 5.6.
- For the purposes of further demonstrating the aggregated results, the teams were also classified according to their temperament makeups based on the MBTI classifications of temperaments presented in Table 5.1. The average scores of the 35 possible temperament combinations for teams are presented in Table 5.7 (which is discussed in the next section).

Table 5.5: Personality ranking for open-ended task

Personality	ENFP	INFJ	INFP	ENFJ	ISFP	ESFJ	ENTP	ESFP	ESTP	ENTJ	INTP	ISFJ	ISTP	ISTJ	ESTJ	INTJ
Score	35	34	34	34	31	30	30	28	28	27	23	22	19	19	15	14

Table 5.6: Personality ranking for structured tasks

Personality	ESFJ	ENFP	ISFJ	ESFP	ENFJ	ENTJ	INFJ	ESTJ	ESTP	ENTP	ISFP	INFP	ISTJ	INTJ	INTP	ISTP
Score	46	41	40	39	39	35	34	31	30	27	26	25	25	23	18	17

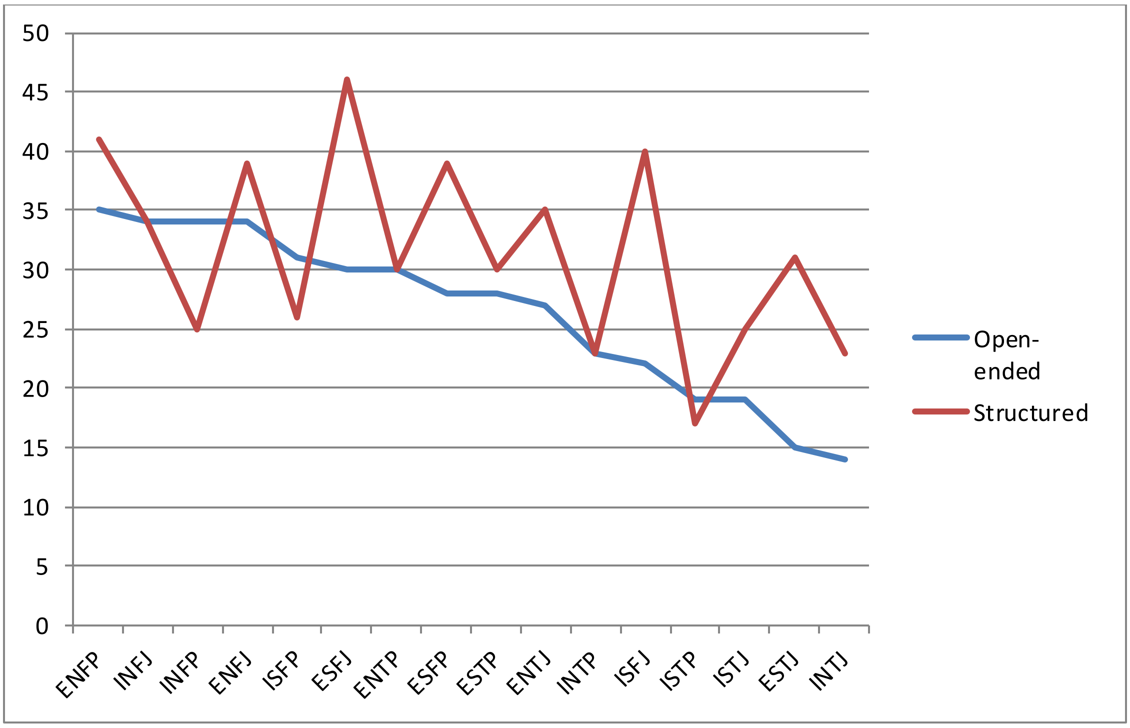

Figure 12: Comparing the performance of personalities in open-ended and structured tasks

Figure 15 shows the average scores for different personalities, which vary depending on whether tasks are structured or open-ended.

Table 5.7: Ranking of combinations in structured task

Rank	Structured task				Score
1	Ideal Seeker	Ideal Seeker	Ideal Seeker	Ideal Seeker	21.86
2	Duty Seeker	Duty Seeker	Duty Seeker	Duty Seeker	21.81
3	Duty Seeker	Duty Seeker	Duty Seeker	Action Seeker	19.67
4	Action Seeker	Duty Seeker	Duty Seeker	Action Seeker	18.65
5	Ideal Seeker	Ideal Seeker	Ideal Seeker	Knowledge Seeker	17.73
6	Action Seeker	Duty Seeker	Action Seeker	Action Seeker	17.35
7	Ideal Seeker	Duty Seeker	Duty Seeker	Duty Seeker	17.34
8	Ideal Seeker	Duty Seeker	Ideal Seeker	Ideal Seeker	17.24
9	Action Seeker	Action Seeker	Action Seeker	Action Seeker	16.51
10	Ideal Seeker	Ideal Seeker	Ideal Seeker	Action Seeker	16.02
11	Action Seeker	Duty Seeker	Duty Seeker	Ideal Seeker	15.78
12	Ideal Seeker	Ideal Seeker	Duty Seeker	Duty Seeker	15.73
13	Duty Seeker	Duty Seeker	Duty Seeker	Knowledge Seeker	15.2
14	Ideal Seeker	Ideal Seeker	Duty Seeker	Action Seeker	14.48
15	Ideal Seeker	Action Seeker	Duty Seeker	Action Seeker	14.37
16	Ideal Seeker	Ideal Seeker	Knowledge	Knowledge	14.16

			Seeker	Seeker	
17	Duty Seeker	Duty Seeker	Action Seeker	Knowledge Seeker	13.74
18	Ideal Seeker	Ideal Seeker	Knowledge Seeker	Duty Seeker	13.62
19	Ideal Seeker	Ideal Seeker	Action Seeker	Action Seeker	13.35
20	Duty Seeker	Duty Seeker	Ideal Seeker	Knowledge Seeker	13.12
21	Action Seeker	Ideal Seeker	Action Seeker	Action Seeker	13.11
22	Ideal Seeker	Ideal Seeker	Knowledge Seeker	Action Seeker	12.46
23	Action Seeker	Action Seeker	Knowledge Seeker	Duty Seeker	12.44
24	Ideal Seeker	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	12.41
25	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	11.71
26	Action Seeker	Duty Seeker	Ideal Seeker	Knowledge Seeker	11.67
27	Action Seeker	Action Seeker	Action Seeker	Knowledge Seeker	11.23
28	Knowledge	Knowledge	Duty Seeker	Duty Seeker	11.1

	Seeker	Seeker			
29	Ideal Seeker	Knowledge Seeker	Duty Seeker	Knowledge Seeker	11.01
30	Action Seeker	Ideal Seeker	Action Seeker	Knowledge Seeker	10.52
31	Action Seeker	Knowledge Seeker	Duty Seeker	Knowledge Seeker	9.94
32	Ideal Seeker	Knowledge Seeker	Action Seeker	Knowledge Seeker	9.89
33	Knowledge Seeker	Knowledge Seeker	Duty Seeker	Knowledge Seeker	9.56
34	Action Seeker	Knowledge Seeker	Action Seeker	Knowledge Seeker	8.77
35	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	Action Seeker	8.47

5.7 Temperament as a Factor in Effective Performance

To examine the impact of team composition in more detail, we grouped agent-based simulation results with respect to temperament that is represented in Table 5.1, which is a generalization of the MBTI scheme. In other words, we merge the 16 personalities as measured by MBTI into one of Keirsey temperament types. For instance, if one agent is labelled as ISTJ, he is relabelled as a Duty Seeker. There are then 35 possible combinations of teams according to temperament, and the team performances of these various combinations are shown for structured tasks and open-ended tasks in Tables 5.7 and 5.8 respectively.

For structured tasks, there appeared to be an advantage in having homogeneity across Duty Seekers and Ideal Seekers (top two results in Table 5.7). In contrast, homogeneous teams of Action Seekers and Knowledge Seekers did not perform well (ranked 9 and 25). In addition, combinations of Duty Seekers and Action Seekers tended to do well (ranked 3 and 4), while combinations of Action Seekers and Ideal Seekers were less successful.

Although Knowledge Seekers did not generally perform well in this task category, their performance was relatively better when they teamed with Ideal Seekers. For example, when a Knowledge Seeker teamed with three Ideal Seekers, it ranked fifth overall.

Table 5.8: Ranking of combinations in open-ended task

Rank	Open-ended task				Score
1	Ideal Seeker	Ideal Seeker	Action Seeker	Action Seeker	17.14
2	Ideal Seeker	Ideal Seeker	Action Seeker	Duty Seeker	17.12
3	Duty Seeker	Ideal Seeker	Action Seeker	Knowledge Seeker	17.07
4	Ideal Seeker	Action Seeker	Action Seeker	Knowledge Seeker	16.72
5	Knowledge Seeker	Knowledge Seeker	Action Seeker	Duty Seeker	16.7
6	Knowledge Seeker	Knowledge Seeker	Action Seeker	Action Seeker	16.37
7	Duty Seeker	Duty Seeker	Ideal Seeker	Ideal Seeker	16.13
8	Duty Seeker	Ideal Seeker	Duty Seeker	Knowledge Seeker	15.97
9	Duty Seeker	Ideal Seeker	Action Seeker	Action Seeker	15.66
10	Knowledge Seeker	Knowledge Seeker	Duty Seeker	Duty Seeker	15.56
11	Ideal Seeker	Duty Seeker	Duty Seeker	Action Seeker	15.24
12	Duty Seeker	Action Seeker	Action Seeker	Knowledge	15.04

				Seeker	
13	Ideal Seeker	Action Seeker	Action Seeker	Action Seeker	14.57
14	Knowledge Seeker	Action Seeker	Duty Seeker	Duty Seeker	14.52
15	Action Seeker	Ideal Seeker	Ideal Seeker	Ideal Seeker	14.27
16	Duty Seeker	Ideal Seeker	Ideal Seeker	Ideal Seeker	14.2
17	Action Seeker	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	14.16
18	Ideal Seeker	Ideal Seeker	Knowledge Seeker	Action Seeker	14.08
19	Ideal Seeker	Knowledge Seeker	Knowledge Seeker	Action Seeker	14.06
20	Duty Seeker	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	13.95
21	Action Seeker	Action Seeker	Action Seeker	Knowledge Seeker	13.83
22	Ideal Seeker	Knowledge Seeker	Knowledge Seeker	Duty Seeker	13.77
23	Ideal Seeker	Ideal Seeker	Knowledge Seeker	Duty Seeker	13.77
24	Duty Seeker	Duty Seeker	Duty Seeker	Ideal Seeker	13.48

25	Duty Seeker	Duty Seeker	Duty Seeker	Knowledge Seeker	12.48
26	Duty Seeker	Duty Seeker	Action Seeker	Action Seeker	9.18
27	Action Seeker	Duty Seeker	Action Seeker	Action Seeker	9.73
28	Action Seeker	Duty Seeker	Duty Seeker	Duty Seeker	8.32
29	Ideal Seeker	Ideal Seeker	Ideal Seeker	Ideal Seeker	7.34
30	Action Seeker	Action Seeker	Action Seeker	Action Seeker	6.58
31	Duty Seeker	Duty Seeker	Duty Seeker	Duty Seeker	5.73
32	Ideal Seeker	Ideal Seeker	Ideal Seeker	Knowledge Seeker	5.66
33	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	4.7
34	Ideal Seeker	Ideal Seeker	Knowledge Seeker	Knowledge Seeker	4.63
35	Ideal Seeker	Knowledge Seeker	Knowledge Seeker	Knowledge Seeker	4.34

The results for the open-ended tasks shown in Table 5.8 indicate that the best combination was two Ideal Seekers with two Action Seekers. In addition the combination of Duty Seekers and Action Seekers teamed with either Knowledge Seekers or Ideal Seekers did well. In general, heterogeneous teams had good performance for these tasks. Homogeneous teams were relatively less successful, and even the best homogeneous team (all Ideal Seekers) was only ranked 29th out of the 35 teams. Overall, the relative success of the combination of Ideal Seekers and Action Seekers was presumably due the fact that the team combined situational openness with active performance. Knowledge Seekers fared poorly; but the combination of Knowledge Seekers with Duty Seekers performed better than the combination of Ideal Seekers with Duty Seekers, and the combination of Knowledge Seekers with Action Seekers did better than the combination of Duty Seekers and Action Seekers.

In summary, the results indicate that not only the team performance rules affect the team performance but also the team member strategies for selecting and leaving a team is crucial for predicting team performance. Also, the strategies need to be different for both open and closed ended tasks.

5.8 Conclusion

In this chapter, a model was developed in the serious game domain in which personality determines the strategy of agents in team formation. The simulations showed the performance of all the possible combinations for two types of tasks which were either open-ended or structured. Similarly to the other two models presented in Chapter 3 and 4, the contribution of this model was not on the particular simulation results, but in demonstrating the ability of the modelling and simulation approaches to generate interesting emergent effects based on MBTI parameterizations. In the next chapter we provide a discussion on the three chapters presented in Chapters 3, 4 and 5.

CHAPTER 6

6 DISCUSSION ON THE ROLE OF TEAM FORMATION IN TEAM MODELING

Previous research showed considering some factors such as skill, knowledge, and personality help managers to select an effective team composition. Although, these factors are important, we believe they are not enough and one additional level of complexity covering self-assembly behaviour needed to be covered. As a result in the three previous chapters we develop three models in three different environments:

1. Chapter 3: A software industry environment with no autonomy for team member selection.
2. Chapter 4: A collaborative learning environments with partial autonomy on team member selection and with an emphasis on knowledge and skill.
3. Chapter 5: A pervasive team-oriented game environment in which no skill and knowledge is required and team members have full autonomy on team member selection.

Our agent-based simulations have demonstrated the effect of individual personalities with respect to a team's performance and collaborative learning, where we have employed the Myers-Briggs Type Indicator (MBTI) to characterize individual personality.

In the first model that is presented in Chapter 4, we have developed a computational model, parameterized on the basis of reports in the academic literature, for measuring the performance of software teams considering their personality composition and skill competency. Based on these aspects, we examined the effect of team formation strategies for task allocation on team performance. We ran agent-based simulations with scenarios with different degrees of dynamic level. We studied whether a resource allocation strategy leads to performance advantages with respect to dynamic tasks. We also examined whether different personality distributions have an effect on two different task allocation methods which are minimising competency and maximizing competency. The effects of the personality distribution and the magnitudes of the impact of each personality were measured.

Based on these experiments, we derived a set of propositions about the conditions under which there are and there are not performance benefits from employing a particular strategy for task allocation. Increasing the degree of changing requirements had a more adverse effect when the strategy of managers is to minimize under-competency compared to when the strategy of managers is to minimize over-competency.

A simple explanation for this result is that the over-competency strategy is an effective strategy when the tasks' requirements are almost static and managers assign some over-qualified employees to the tasks that make them sure the tasks will be performed successfully. However, in a very dynamic environment, they may assign some over-qualified employees to some tasks, and over time the requirements of some other tasks may increase so that the required employees are busy with some other tasks and are unavailable for managerial selection for new teams. In addition, for most cases of the personality distribution, the two strategies did not have significant differences; however, for a few scenarios some exceptions were observed.

The results of the experiments in this model demonstrated that different strategies for task allocation are suitable in different situations. However, in most of the contemporary platforms, managers do not have total autonomy in selecting team formation strategies. They are dealing with self-assembling teams which have a degree of agency, and understanding the mechanism behind this self-assembling behaviour helps managers and designers to promote and motivate particular strategies in a particular situation. The self-assembly behaviour is relatively unexplored area and in the next chapter of the thesis, we develop a model of self-assembly teams in which the behaviours of the components of the teams are mainly motivated by their personality.

In the second model presented in Chapter 4, we chose a collaborative learning environment. A simulation environment helped provide an understanding of the relationship between group formation and the learning process. As a result, we have developed a model that shows how people may grow their knowledge and skill in two different team-formation mechanisms which are team formation based on skill and based on knowledge-credibility.

The results of our collaborative learning simulations showed that although team assembly based on skill ended up with good performance, they are not necessarily successful in developing their knowledge and collaborative learning. In particular, knowledge increased more in the credibility-based team-formation mechanism. We also investigated the effects of temperament (personality) on team performance for both team-assembly mechanisms. This example, again, highlights the importance of self-assembly in team modelling. In these models an agent has autonomy to choose his team members based on his perception about either their knowledge or skill.

In the third model that is presented in Chapter 5, for the game environment, we have used our modelling framework to demonstrate how one can investigate the effect of various personality interactions on overall team performance with respect to four-person teams. Our agent-based simulations have demonstrated how some combinations of temperaments can enhance the overall efficiency of a team, while other combinations can prove to be detrimental. In this model, the team members have autonomy to choose their teammates and their decision about selecting a team was purely related to their personality.

6.1 A Decision Support System Framework for Teamwork Modelling

Our main goal in these three chapters was to demonstrate the importance of including team formation mechanisms in the team formation models in three environments, which are software projects, collaborative learning, and games. However, we have contributed to a multi-agent framework that can be used for researchers and managers and designers to investigate the effect of task allocation strategies in a real-world environment.

As we observed in these experiments, configuring a team merely by considering their skill and fitting into the job is not sufficient, and having strategies for team formation in a dynamic environment is necessary. Contemporary teams are self-assembling, and the components of **these** teams have a degree of autonomy. However, managers and designers by selecting appropriate strategies can influence the team formation. We believe Decision Support Systems on teamwork should cover beyond the ability of individuals and the match between team members. We propose a Decision Support System that addresses all the complexities in the team work modelling and can be applied in crowdsourcing websites, computer-supported cooperative work (CSCW), groupware, Computer-supported collaborative learning (CSCL), and physical organizations.

Using cognitive and psychological tests such as personality tests helps managers to predict the behaviour of their employees. It could be more useful for project managers to apply the results of personality tests to build virtual teams. By simulating possible behaviours of individuals, we can analyse what could happen when people with specific personalities interact with each other. Such tools could help managers, designers of crowdsourcing websites, and the teachers using virtual learning environments to find answers of some questions such as following:

- What happens for the future team composition if two people with specific personalities are working together on a particular task?
- What are the best possible team configurations for avoiding future conflicts?
- How does recruiting or firing some with specific personalities affect team behaviour in the long term?
- How does adding some tasks with specific characteristics affect the performance in the long term?
- How does adding some motivations and regulations for self-assembling behaviour improve the overall efficiency of the teams?
- What is best team composition in an environment with a particular dynamism level?
- Who are the best employees with different attributes in terms of personality and skill?
- What will be the skill and knowledge of teams in the future in an environment with a particular personality distribution and a particular team formation mechanism?

In the following table we summarise which of the three models is a best fit to answer the above questions:

Table 6.1: The questions addressed by Chapters 3, 4, and 5

Question	Chapter 3	Chapter 4	Chapter 5
What happens for the future team composition if two people with specific personalities are working together on a particular task?		■	■
What are the best possible team configurations for avoiding future conflicts?	■		
How does recruiting or firing some with specific personalities affect team behaviour in the long term?	■		
How does adding some tasks with specific characteristics affect the performance in the long term?	■	■	■
How does adding some motivations and regulations for self-assembling behaviour improve the overall efficiency of the teams?	■	■	■
What is best team composition in an environment with a particular dynamism level?	■		
Who are the best employees with different attributes in terms of personality and skill?	■		■
What will be the skill and knowledge of teams in the future in an environment with a particular personality distribution and a particular team formation mechanism?		■	

As we demonstrated in these three chapters, a comprehensive framework must cover the performance of a team composition and a model for self- assembly team formation. The self-assembly part is neglected in the prior work by other researchers in this area. To bridge this gap, in the rest of this thesis, we develop models that predict the team composition and team performance of self-assembly teams.

6.2 Conclusion

In Chapters 3, 4 and 5 we presented three models that demonstrate the undeniable role that including team formation mechanism can play in team performance, and in this chapter we discussed how these models can be used in a decision support framework for researchers, managers and website designers.

We believe there is no universal and unique DSS configuration that can be applied in all the organisations. The situational forces such as organizational and cultural forces and task structures must be taken into consideration before generalizing the proposed rules between personality and performance. Regarding that, we discussed our proposed framework for building an agent-based model where the results can vary in different domains. Researchers and managers might change rules, formulas, and the constraints in the team formation mechanism section based on situational forces.

We wish to note here that what we have presented in part 2 of this thesis (Chapters 3-5), as a contribution is not so much the specific simulation results, but a modelling and simulation approach that can demonstrate interesting emergent effects based on MBTI parameterizations. This parameterization can be set for the specific contextual circumstances to examine sensitivities in this area.

Understanding the mechanism behind team formation of the self-assembly teams enables managers and designers in different platforms, especially in computer-based platforms, to help the team members by providing regulations and motivations in the team-assembly process. Based on our results in this chapter about modelling team behaviour on the basis of individuals' personality and the importance of self-assembly in team modelling, in the next part of the thesis (part 3), we develop a team self-assembly model.

In this part of the thesis (Chapters 3-6), we demonstrated why understanding team behaviour requires a higher step that is understanding assembly of project teams. In Chapter 7, we develop a self-assembly model based on the team members' personality types, and we explain how teams evolve in the ad-hoc team environment in the software project area.

CHAPTER 7

7 MODELING THE EFFECTS OF PERSONALITY ON TEAM FORMATION IN SELF-ASSEMBLY TEAMS

In the previous part of the thesis, we discussed the role of team formation mechanism in understanding team performance. In this chapter, we describe a *self-assembly team formation* model in the software development area. A model is developed to demonstrate how temporary teams evolve based on the personality of team members. Although specific task-related skills are important in connection with choosing project team members, we omit those explicit considerations here so that our study can concentrate on the effects of personality and temperament. Some results of this chapter are published in (Farhangian et al., 2016a).

This chapter is organized as follows: Section 7.1 presents our proposed rules and principles about team-formation mechanisms and our agent-based model. Section 7.2 is a presentation of some general experiments and results based on our team-formation model and discusses psychological personality models and also reviews the literature about the relationship between personality and team formation. Section 7.3 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 models' principles. Section 7.4 contains the conclusion.

7.1 Team Formation Process

There are two types of roles in the temporary self-assembly teams, which we call 'requesters' and 'contributors' (Aitamurto 2015). *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. The *contributors* are the recruited people who contribute to the tasks. As we discussed earlier, personality is one of the main indicators of human behavior. As a result, we believe the personalities of the individuals in the team (both requesters and contributors) have a major impact on their team's overall behavior. A schematic representation of the self-assembly process and the interactions between the requester and the contributor is shown in Figure 16.

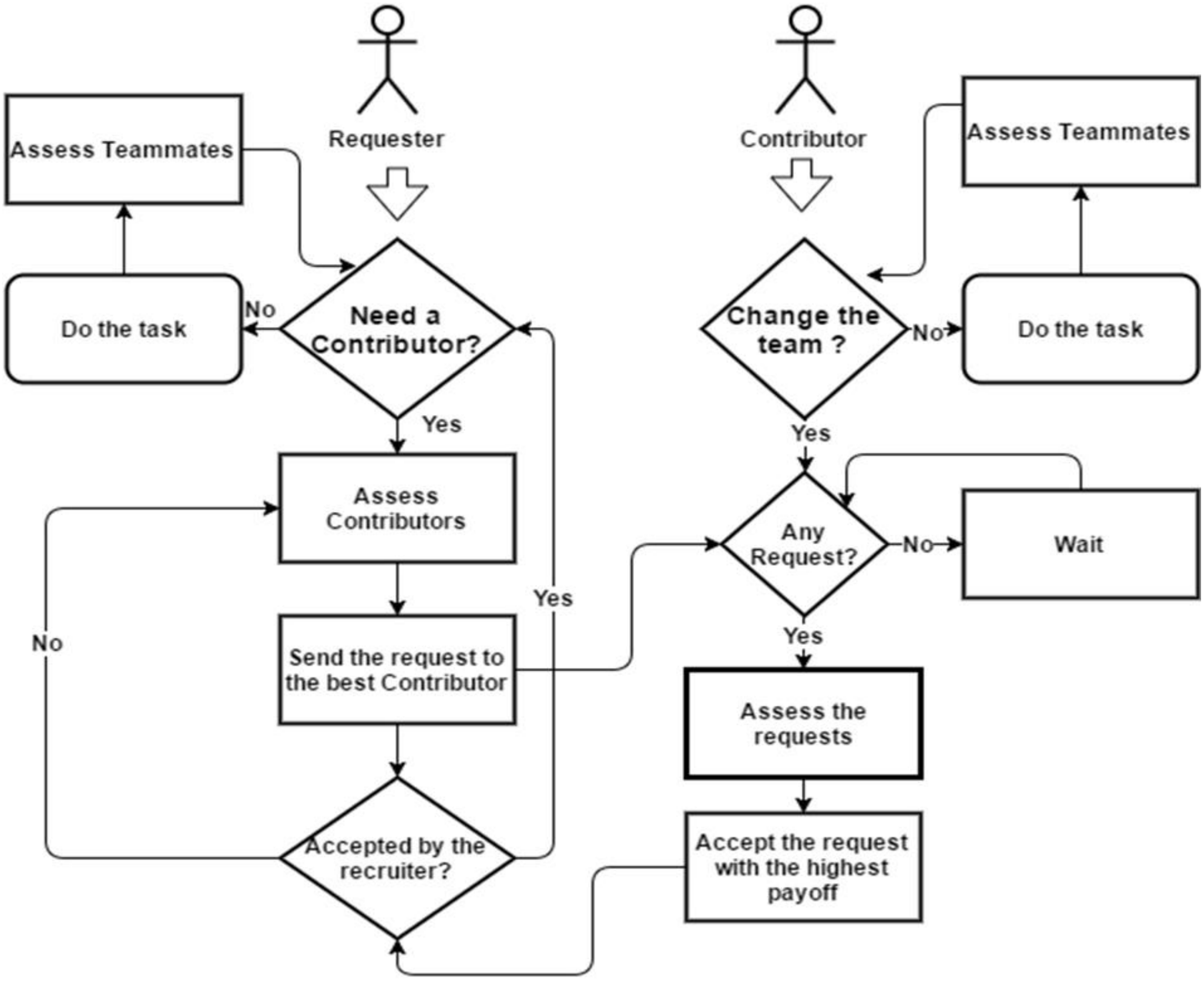

Figure 16: Team recruitment involving requesters and contributors.

In the process depicted in Figure 16, the two types of agents update their beliefs about other agents over time. This belief consists of two parts: familiarity and awareness of previous performance. This belief update affects their decision every time they choose a new team member (as a requestor) and the decision to join a new team (as a contributor). The rest of this section describes in more detail the team formation process presented in Figure 16.

In this connection, clearly any previous collaboration experience is one of the main factors that affects the self-assembly mechanism, as suggested by other researchers (Guimera, 2005), (Cummings & Kiesler, 2008), (Hahn et al., 2004), (Roberts et al., 2006) and (Ruef et al., 2003). As a result, group composition and factors that determine the performance of groups must be included in any work that tries to model the coalition formation.

In addition to any previous experience among potential group members, interpersonal attraction (i.e. attitudinal positivity toward another person) motivates human beings to connect with others. The literature has explored a variety of ways that people are attracted to one another and some examples include, age, race, sexual orientation, personality, attitudes and beliefs (Wax, 2015). However, in volatile environments where new teams must be rapidly assembled, some locally-known knowledge must be used to construct the team, and this often comes down to local familiarity with past performances and awareness of personality types. Thus we have constructed our model on this basis and assume agents' individual decisions about team formation are determined by two factors: familiarity and past success.

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

We assume the importance of these factors is different for people with the different personalities. Sensor types pay attention to the immediate data from their five senses and direct experience. They focus on what is practical, immediate, and real. In contrast, iNtuitive types pay less attention to immediate data and tend to concentrate on longer-term goals. iNtuition is applied to explore the unknown possibilities and implications that are not readily apparent (Ginn & Sexton, 1990). As a result, we assume that Sensing types are more likely to record their past experiences about team performance, which will affect their measures of familiarity towards others.

The assumptions that we have made in this chapter are summarized in Table 7.1. These assumptions are based on the literature that we have discussed in Chapter 2.

Table 7.1: Assumptions about self-assembly team formation

Personality	**Assumption**
iNtuition-Sensing	Sensors pay attention to the immediate data from their five senses and direct experiences. They focus on what is practical, immediate, and real. In contrast, iNtuition types pay less attention to immediate data and tend to concentrate on future outcomes. As a result, we assume that Sensing types are more likely to record their past experiences about team performance.
Thinking-Feeling	In connection with Thinking and Feeling (the T-F dimension of MBTI), Feeling people are more likely to be concerned about the impacts of their decisions in connection with their social context. Thinkers, on the other hand, follow their objective principles and standards that are less influenced by social context. T-people are logical, and F-people make decisions based on their heartfelt concerns. For this reason, 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	How often agents decide to alter their team is determined by the Judging or Perceiving aspect of personality. Judgers (J-people) prefer to operate in a planned and settled fashion, while Perceivers (P-people) can operate in a more flexible and spontaneous way – they prefer to remain open to new information that may come up at any time. For this reason, we assume team

	members with Judging personalities are more likely to refrain from changing their team and prefer to continue with the previous team, while employees with Perceiving personalities are more flexible and more likely to change their teammates.
Extraversion-Introversion	The sociability of a person can also be a factor in the team formation process. This sociality relates to the E-I (Extraversion vs. Introversion) dimension of MBTI. Being Extraverted determines the degree to which agents are outgoing and have a chance to meet new people and be familiar with them. In our model, we assume employees with Extraverted personalities connect with more people in their social network.

To form teams, we developed an algorithm comprising requester and contributor agents. If a requester needs contributors (shown on the left hand side of Figure 16), it assesses the available contributors' performance and sends the request to the top contributor. If the contributor accepts the request and no additional contributors are required to complete the task, then the team proceeds to perform the task. If more contributors are required, the process continues until the required numbers of team members are recruited.

When a contributor is requested to join (shown on the right hand side of Figure 16), this request can come from the previous team that it was a part of or from a new requestor. The contributor can decide to continue with the previous team or can decide to join a new team. If it decides to be a part of the old team, the contributor performs the task with the old team members. If the contributor decides to join the new team, it needs to assess all the requests received to join new teams. The contributor decides to join the team that has the potential for the best payoff (based on previous performance knowledge). From the above discussion, it is evident that a mechanism to score the requesters and contributors is required. This mechanism is discussed below. In our system, both of the requestors and contributors try to be part of a team with the highest collective score. After finishing each task, agents assign a value to their teammates based on their team's performance in the task. Also, they are constantly updating their familiarity with others.

In our model a requester j assigns value C_{ji} to a contributor i as presented in Formula 7.1.

$$C_{ji} = \frac{\left((NS_j * v_{ji}) + (TF_j * familarity_{ji})\right)}{NS_j + TF_j} \qquad (7.1)$$

In this formula, NS_j is the iNtuition-Sensing personality index of the requestor j. v_{ji} is the performance value that is maintained by j with respect to i and is discussed further below in Formula 7.5. TF_j is the Thinking-Feeling personality dimension index of the requestor j, and $familarity_{ji}$ represents the past interaction of agent j with agent i and is calculated by means of Formula 7.2, below. Agent i receives the request and uses the same formula to make a decision about accepting the request or not. Thus the same formula is used for both assessing the requestors and assessing the contributors, which are mentioned in the "Assess" components in Figure 16.

7.1.1 Familiarity

Apart from performing a specific task, agents interact with other teammates more generally (e.g. hallway conversations). Thus two agents in the same organization constantly improve their familiarity with respect to each other. However, the probability of their interaction is based on the extent to which they have an Extraverted personality (Bradley et al., 2013). Thus the continual familiarity improvement is not similar for all the agents and is related to their sociability.

This sociality is affected by the E-I (Extraversion vs. Introversion) dimension of MBTI. Being Extraverted determines the degree to which agents are outgoing and have a chance to meet new people and be familiar with them. In our model, we assume employees with Extraverted personalities connect with more people in their social network. In Formula 7.2, EI indicates the Extraversion-Introversion personality scale of the agents. The familiarity of agent i, at time t, from the viewpoint of agent j is given by $familarity\ (t)_{ji}$ which is calculated as follows:

$$familarity\ (t)_{ji} = familarity\ (t-1)_{ji} + \left(1 - \frac{EI_i + EI_j}{200}\right) \qquad (7.2)$$

The value of familiarity computed using Formula 7.2 is used in Formula 7.1. The second term in Formula 7.2 $\left(i.e\ 1-\frac{EI_i+EI_j}{200}\right)$ has maximum and minimum values of 1 and 0, respectively. The increment to the previous familiarity value is the difference between 1 and the combined E-I values divided by the combined maximum E-I value possible (100+100=200). If both parties are Introverted (100, 100 respectively), then the new familiarity value will remain the same. If both parties are Extraverted with the scores of 0 and 0 respectively, then the new familiarity score will increase by one. If one is more Extraverted than the other (say 50 and 100 respectively), the second term of Formula 7.2 will evaluate to (1-(150/200)) = 0.25. In other words, the familiarity score will in this case increase by 0.25.

7.1.2 Team Performance

Past team performance is the second key factor affecting group self-assembly, and there has been interest in evaluating how personality affects team performance (LePine, et al. 2011). The studies in this area have led to two contrasting views: those who believe heterogeneous teams are more efficient and those who believe homogeneity positively affects team performance.

TPD, which measures team heterogeneity and homogeneity, is a significant measure in this context. 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 and open ended tasks.

In Chapter 5, these two types of tasks are defined. In Chapter 7, we have made a simplified assumption about the relationship between the tasks' type, the personality composition of the team, and team performance. This assumption will be tested in the next chapters.

Wiersema et al. (1992) noted that team homogeneity brings about a shared language among team members and improves integration and communication frequency, suggesting homogeneous teams are likely to perform better on tasks that require high coordination. In contrast, Bantel et al. (1994) 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 the following:

- For structured tasks, low TPD is likely to have a positive effect on team performance.
- For open-ended tasks, high TPD is likely to positively affect team performance.

These assumptions are summarized in the following formula:

$$Performance_b = \beta * (100 - |Heterogeneity_{\,l} - Tasktype_b|) \tag{7.3}$$

β is a coefficient that indicates the capabilities of team members other than their personality. Of course performance can involve other factors, such as skill or experience as mentioned earlier, and these could be incorporated into a more sophisticated formula for performance if suitable data is available. But heterogeneity is a key factor, and in this thesis where we are focusing on personality effects and do not wish to cloud the issue with too many extra factors, we restrict performance to that presented in Formula 7.3. For the sake of simplicity, β is taken to be 1 in the experiments described here.

In this formula, $Heterogeneity_{\,l}$ 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 7.4. $Tasktype_b$ represents the nature of the task that shows the degree to which the task is open-ended or structured, and it 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.

In formula 7.4, $\overline{S_{EI,J}}$, $\overline{S_{NS,l}}$, $\overline{S_{JP,l}}$ and $\overline{S_{TF,l}}$ represent the standard deviations of team l with respect to Extraverted/Introverted (E-I), iNtutive/Sensing (N-S), Thinking/Feeling (T-F) and Judging/Perceiving (J-P), respectively.

$$Heterogeneity_{\,l} = \frac{\overline{S_{EI,l}} + \overline{S_{NS,l}} + \overline{S_{JP,l}} + \overline{S_{TF,l}}}{4} \tag{7.4}$$

In our model, agents update their performance value v_{ij} with respect to another agent whenever they cooperate in a team with each other, as presented in Formula 7.5.

$$v_{ij}(t) = Performance_b + v_{ij}(t-1) \tag{7.5}$$

In Formula 7.5, v_{ij} indicates that the value that agent i assigns to agent j after performing a task. v_{ij} can take one of three values: 1 (if the performance is successful), 0 (if the task is still active), or -1 (if the performance was unsuccessful). And, as mentioned above for software tasks, a heterogeneous team is likely to positively affect team performance. So,$Performance_b$ which indicates our characterization of the team's performance in task b, is presented in Formula 7.3. As an example if heterogeneity of a team in terms of E-I, N-S, J-P, and T-F is 25, 50, 60, 50, respectively, then $Heterogeneity_{\,l}$ is the average of these four numbers which is 40.

7.1.3 Team Commitment

Since most teams are temporary, agents constantly reshape their teams. After each task, requesters might decide to fire a contributor, and equally, contributors might decide to leave the job. How often agents decide to alter their team is determined by the Judging or Perceiving aspect of personality. Judgers (J-people) prefer to operate in a planned and settled fashion, while Perceivers (P-people) can operate in a more flexible and spontaneous way – they prefer to remain open to new information that may come up at any time. Perceivers like to keep their options open and may often avoid being attached (Bradley et al., 2013). For this reason, we assume team members with Judging personalities are more likely to refrain from changing their team and prefer to continue with their existing team, while employees with Perceiving personalities are more flexible and more likely to change their teammates.

As a result, the Judging and Perceiving personality dimension can affect this decision, and the probability of leaving a group is represented in Formula 7.6. In this formula, Co_i is the probability of leaving a team or firing a contributor, and JP_i is the Judging personality index of agent i.

$$Co_i = \frac{JP_i}{100} \tag{7.6}$$

In this model, the number of team members does not change and in the case of firing or voluntary leaving, requesters recruit another employee. In our model, every time that a task is completed, each team member (i.e. both contributors and requesters) needs to make a decision either to continue with their current team or to move and do the next task with another team. This decision is related to their Judging-Perceiving personality dimension.

There are thus six principal factors in our model that affect team performance: familiarity, past performance, and the four personalities as measured by MBTI measures.

7.2 Experiments and Results

We developed an agent-based simulation with two main goals. Firstly, we investigated the correlation between agents' personalities and their scores (i.e. the average performance of their teams). Secondly, in order to see the evolution of teams' compositions in the temporary teams, we studied the most repeated team compositions.

In the initial settings, 100 requesters and 1000 contributors are asked to perform 100 tasks. Four numbers between 0 and 100 are randomly assigned to each personality dimension for both requesters and contributors. 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, one hundred new tasks are added to the environment, and the simulation is terminated after 100-time steps. To account for the randomness of the assigned values, performances are reported as averages over 100 simulation runs.

Similar to our representations of personality of agents in previous chapters, 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.

Table 7.2 shows the correlation matrix for each of the MBTI dichotomies, and the performances, in the three dimensions of E-I, T-F and J-P correlations, are significant at the 0.05 level. For instance, the p-value between E-I dimension and personality is 0.0043, which is less than 0.05, and these two variables are negatively correlated with -0.272. It means that performance is negatively correlated with Introversion and thus positively correlated with Extraversion. In Table 7.2, the correlation with the second letter of personality is measured. As a result, the correlations with Introverted (I), Sensing (S), Feeling (F) and Perceiving (P) have been presented in this table.

Table 7.2: Correlation between the personality and performance

Personality	**E-I**	**N-S**	**T-F**	**J-P**
Correlation	-.272	.009	-.186	.226
P-value	0.0043	0.16	0.002	0.00079
Is the p-value statistically significant? If yes, at what level?	Yes ($p < 0.05$)	No	Yes ($p < 0.05$)	Yes ($p < 0.05$)

In summary, it was observed that the agents' scores are positively correlated with Extraversion, Thinking, and Perceiving personalities (with $p < 0.05$), as shown in row 4 of Table 7.2. A brief and simple explanation for each one is as follows. For agents with Extraverted personalities, having more connections and knowing more people in the social network played a positive role in team performance (0.272). Agents with Feeling personalities put more weight on their familiarity factor for choosing teammates, and this can lead to picking a less effective team member with poor performance. Agents with Perceiving personalities have a higher probability to experience working with new members and increase their knowledge about them. As a result, compared to Judgers, they are more likely to find successful teams. Surprisingly, there was no significant correlation between Sensing personalities and agents' scores. We expected their emphasis on previous team experience would help them find the best matches eventually. It appears, however, that because their knowledge and experience are incomplete due to a limited experience, they are less successful in selecting team members.

In addition to the observations above, we were interested in investigating the most frequent team compositions. To explore this further from our simulation data, we added the labels "Very Low", "Low", "Medium", "High", and "Very High" to the variables about team personality (i.e. TPD-EI, TPD-NS, TPD-TF, TPD-JP, TPE-EI, TPE-NS, TPE-TF, TPE-JP). We divided the personality into 8 equal categories. For instance, TPE-EI very low means the team is very Extraverted, and very high means the team is very Introverted. Observations are summarized in Figures 17 and 18. These graphs show the percentage of each configuration in personality composition. For example, in Figure 17, the first bar shows TPE-EI (TPE in the Extraverted-Introverted dimension), and it indicates that 45%, 21%, 12%, 9% and 18% of the teams had Very Low, Low, Medium, High and Very High values of TPE-EI, respectively. Generally, it shows that individuals mostly prefer to form teams with low TPE-EI. In contrast, Figure 18 shows that for open-ended tasks, individuals prefer to form teams with high TPE-EI. These results will be further discussed in the next chapters, where we compare them with the particular domain presented in the next chapters.

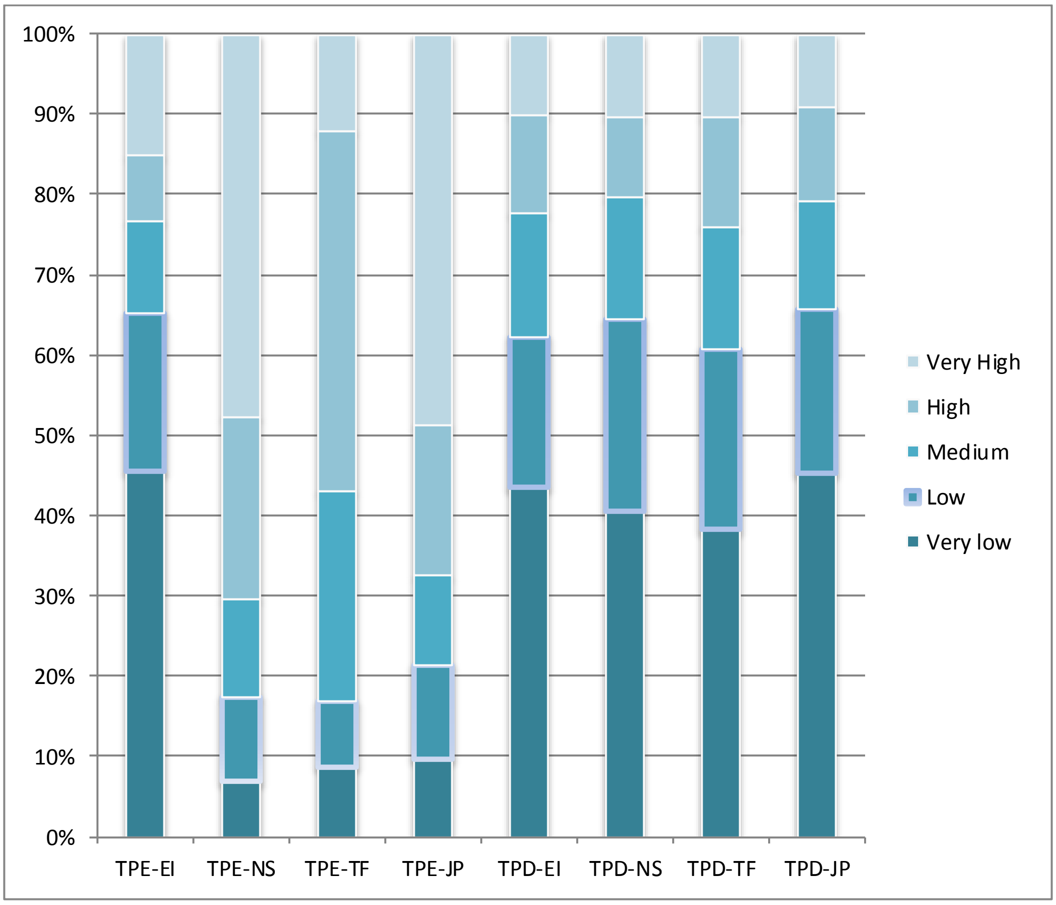

Figure 17: Team composition (for structured tasks)

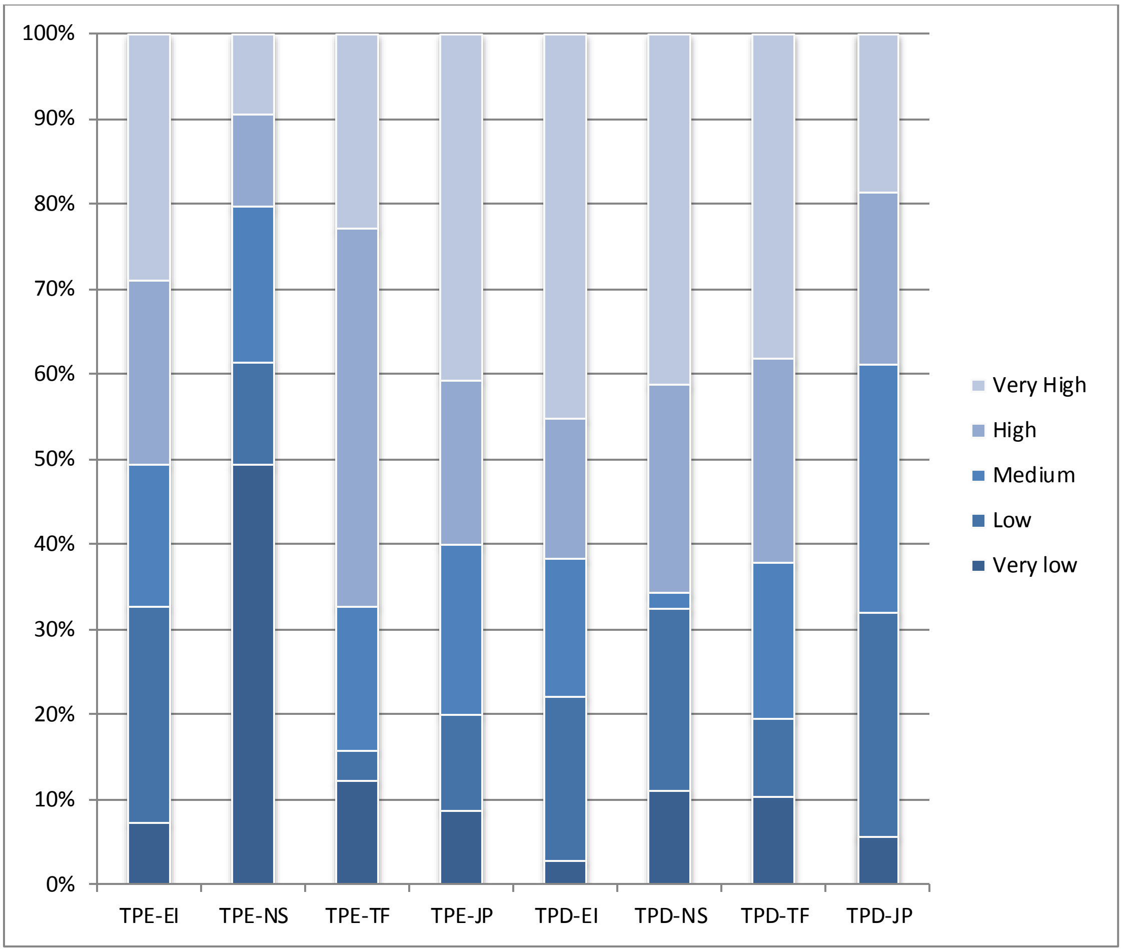

Figure 13: Team composition (for open-ended tasks)

7.3 Conclusion

Regarding the mechanisms behind the formation of the self-assembly teams, in this chapter, we developed a model that derives the formation of a team with respect to six features: familiarity, past performance, and the four personalities as measured by MBTI measures. Moreover, by using agent-based simulation, we conducted some experiments to predict the effect of personality type on team performance and predict the most repeated team compositions.

This model will be the main focus of the rest of this thesis, and how it will be used is discussed in Chapters 9 and 10. In those chapters we will describe our application of our model to a specific domain of software engineering, the Python Enhancement Proposals (PEPS). The various aspects of data analysis, data gathering, and processing in connection with this exploration are discussed in the next chapter.

CHAPTER 8

8 DATASET FOR INVESTIGATING SELF-ASSEMBLY TEAMS IN SOFTWARE DEVELOPMENT

In order to demonstrate the utility of the team formation model that is developed in Chapter 7, we have chosen a real case study of the Python Enhancement Proposal (PEP) process. The data for this project was extracted from publicly available information about Python Enhancement Proposals (PEPs)[1]. PEPs are documents that contain information about changes made to the Python programming language. A PEP (and progress it into various stages from draft to acceptance or rejection) is performed by a team of developers. These are self-assembled teams where developers form a team with those who are passionate about an improvement to the Python language.

The primary goal of the rest of this thesis is comparing the result from the agent-based model constructed (and executed as simulations) with real data in PEPs (i.e. composition of teams that were formed in PEPs). The input to the model is the pool of developers available and their respective personality types. While the developer names involved in PEPs are known (from public archives), their MBTI personalities are not known. We need an efficient and unobtrusive method of inferring personality types of these developers. Since we do not have access to the personality of PEPs developers (and soliciting this information is impractical), this thesis also has contributed in developing a computational model that determines the personality of people based on their writing styles. We have developed a computational model to determine the personality of people from their texts.

In this connection, we describe three main processes with the ultimate aim of inferring a personality type of a Python developer:

- Gathering public data.

[1] https://www.python.org/dev/peps/pep-0001/

- Finding relationships between personality and text usage.
- Finding the personality of PEPs developers.

For step 1, we gathered the written pieces of text by various users and the information about the Myer-Briggs Type Indicator (MBTI) profiles of those users who self-reported their personality profiles on social networking websites such as Quora, College Confidential and Reddit. Then in step 2, we found the correlation between the Linguistic Inquiry and Word Count (LIWC) dimensions and MBTI personalities. LIWC is known as an influential approach that has a high appeal for social scientists in need of a tool to work with texts (Gottschalk and Bechtel, 1998; Bollen et al., 2010). LIWC unlike some other similar methods such as MRC database (Wilson, 1988), does not characterize words by using continuous scales, but instead classifies entries categorically. Since this research is mostly interested in categories, LIWC has been preferred over the similar methods. LIWC is based on counting function words and uses a psychometrically-based dictionary to divide the different counts into meaningful dimensions. The program searches for more than 4,500 words and word stems and categorizes them into four categories:

1. Linguistic processes (e.g., Personal Pronouns, Adverbs, Prepositions).
2. Psychological processes (e.g., Social Processes, Positive Emotion, Negative Emotion).
3. Personal concerns (e.g., Work, Achievement, Leisure).
4. Spoken categories (e.g., Assent, Non-fluencies, Fillers).

A formula based on these findings was constructed that can predict the personality type of individuals. Third, using the text written by developers involved in different Python Enhancement Proposals (PEP) we predict their personalities were predicted. The results in this chapter agree with those of (Farhangian et al. 2016b).

8.1 Personality and Text Analysis

As we discussed in Chapter 2, several studies have found associations between personality and text usage. In order to address the following limitations in the previous studies, we developed a model of personality based on the text usage.

- There is no study to focus on the relationship between LIWC and MBTI. However, Lee et al. (2000) introduce correlations between the Korean version of Linguistic Inquiry and Word Count KLIWC and Myers-Briggs types, but their studies is limited to the Korean language.
- Previous studies collected texts under laboratory settings. As we discussed earlier, people may not express their real feelings, morals, and values when they do not choose a topic to write about. Behaviour is discriminative versus consistent across situations; and the contexts of assignments and scientific articles do not cover a good variety of situations. Also, assignments and scientific articles in the laboratory settings may mainly relate to verbal ability rather than personality.
- In the previous studies the sizes of samples are not considerable and each writing sample is less than a few thousand words. Moreover, these data are gathered from a small number of participants that limit the results.

To overcome these issues, in this study, we extracted data from social networking websites to reveal the relationship between these texts and the MBTI personalities of their writers. Unlike the laboratory settings, in the social networking websites, people are free from constraints that a particular preselected topic places on them, since they are free to choose the discussion topics. And unlike assignments they focus on their opinion rather than showing their intelligence and verbal ability. In addition, social networking websites are rich in textual styles, since they enable users to create different text contents in the forms of posts (e.g. comments, tweets, blog entries, and social-media messages in sites such as Facebook).

8.2 Method and Data Extraction

Our method for extracting insights about the relationship between Python developers and their personality consists of 3 main steps as indicated in Section 8.1. A detailed description of these three steps is provided below.

Step 1 – Data gathering; the first step involves extracting data from the social networking websites where people report their MBTI personalities. In most of the social networking websites, people do not care about their spelling and grammar in their writing, so it leads to various types of ambiguities. To avoid this issue, we used a popular social networking website (*quora.com*) in which people cannot be anonymous or use fake names. Using one’s real name and the Quora culture increase accuracy in terms of spelling and correct grammatical constructions of sentences. Also, to validate our findings, we explored two other popular social networking websites: *reddit.com* and *collegeconfidential.com*.

In Quora, discussing and reporting one's personality as measured by MBTI is popular. We identified users who reported their personalities and extracted information about their personalities. In addition, we posted three questions on the site and got 32 answers and asked the users to report their personalities to enrich our data. In order to investigate the reliability of this distribution, we took similar steps for the other two sites and extracted data from users - College Confidential ("collegeconfidential," 2015) and Reddit ("Reddit," 2015).

Step 2 - Finding relationships between personality and text usage; in this step, we extracted the texts of the Quora users from their responses to the questions about their personality as measured by MBTI. Users' texts are analysed with the LIWC tool and the value for all the 80 LIWC dimensions are identified for each user. The LIWC tool takes an input text file and returns files containing word counts for each of the LIWC dimensions of that text. After generating the value of all the variables in our Quora samples, we measured correlations between personality and these variables. These correlations enable us to develop a computational model that determines the personality of people from their texts. To validate this computation model, our formula was cross tested in Reddit and College Confidential data.

Step 3 – Identifying the personality of PEP developers; in the third step, we conducted an analysis of the PEPs which were developed by teams. We gathered the text of all PEP team members from their public activities on the internet such as their blog posts and tweets. Then our new computational model was employed to discover the personality of each team member.

8.3 Results and Discussions

In Quora, we identified 393 users who reported their personality. The large size of the dataset enabled pervasive correlations to be identified for a broad range of LIWC variables. The distribution of personality among users was different from some reports about the distribution of personality (e.g. (The MyersBriggs Foundation, 2015)). So, we compared the distribution of personality with two other social networking websites. This comparison allows us to assess whether our Quora data is reliable, and it was shown to follow a similar trend to the other social networking websites.

Table 8.1 Number and percentage of each personality type in the studied samples

Personality	Quora		College Confidential		Reddit	
	Number	Percentage	Number	Percentage	Number	Percentage
ESTJ	8	2.03%	10	5.4%	1	2.6%
ISTJ	12	3.05%	11	5.95%	2	5.13%
ISFJ	4	1.02 %	6	3.24%	1	2.56%
ESFJ	5	1.3%	5	2.7%	0	0%
ESFP	9	2.3%	6	3.24%	0	0%
ISFP	5	1.3%	1	0.54%	0	0%
INFP	52	13.3%	5	2.7%	3	7.69%
INFJ	44	11.2%	12	6.49%	2	5.13%
ENFJ	18	4.6%	12	6.49%	5	12.82%
ENTJ	31	7.9%	12	6.49%	4	10.26%
ISTP	8	2.03%	4	2.16%	2	5.13%
INTP	60	15.3%	27	14.59%	7	17.94%
INTJ	59	15.01%	43	23.24%	5	12.82%
ESTP	6	1.53%	4	2.16%	1	2.56%
ENFP	30	7.63%	14	7.57&	1	2.56%
ENTP	42	10.69%	13	7.03%	5	12.82%
Total	393	100%	185	100%	39	100%

In order to investigate the reliability of this distribution, we took similar steps for the other two sites and extracted MBTI reports from 185 users in College Confidential and 39 users in Reddit ("Reddit," 2015). As these data from College Confidential and Reddit were analysed and compared with Quora data, we become more confident that the selected cases of Quora represent a reliable sample. The numbers and percentages of each MBTI profile of data are presented in Table 8.1.

Table 8.2 illustrates the similarity across three social networking websites in a summary fashion. In all the websites, the Introverted types were slightly more than the Extraverted types (59%, 56% and 62% were Introverted for College Confidential, Reddit and Quora, respectively). iNtuitive types were by far more numerous than Sensing types (75%, 82% and 85% of users were iNtuitive in College Confidential, Reddit and Quora, respectively). Thinkers were slightly more numerous than Feelers (67%, 69% and 56% were Thinkers in College Confidential, Reddit and Quora, respectively), and Judgers and Perceiver's were almost equal (40%, 49% and 54% were Perceiving, in College Confidential, Reddit and Quora, respectively). We found that this distribution differs from more general distribution. For example, unlike the distributions reported in (The Myers Briggs Foundation, 2015) that is presented in Table 8.3, in the social networking websites N (iNtuition) is dominant and it makes up 75%, 82% and 85% of users in College Confidential, Reddit and Quora, respectively as presented in Table 8.2. These results suggest that people active in social networking website are almost different from the average people. Nevertheless, it should be noted that because of small, the statistical power is not significant and the results have not been confirmed statistically.

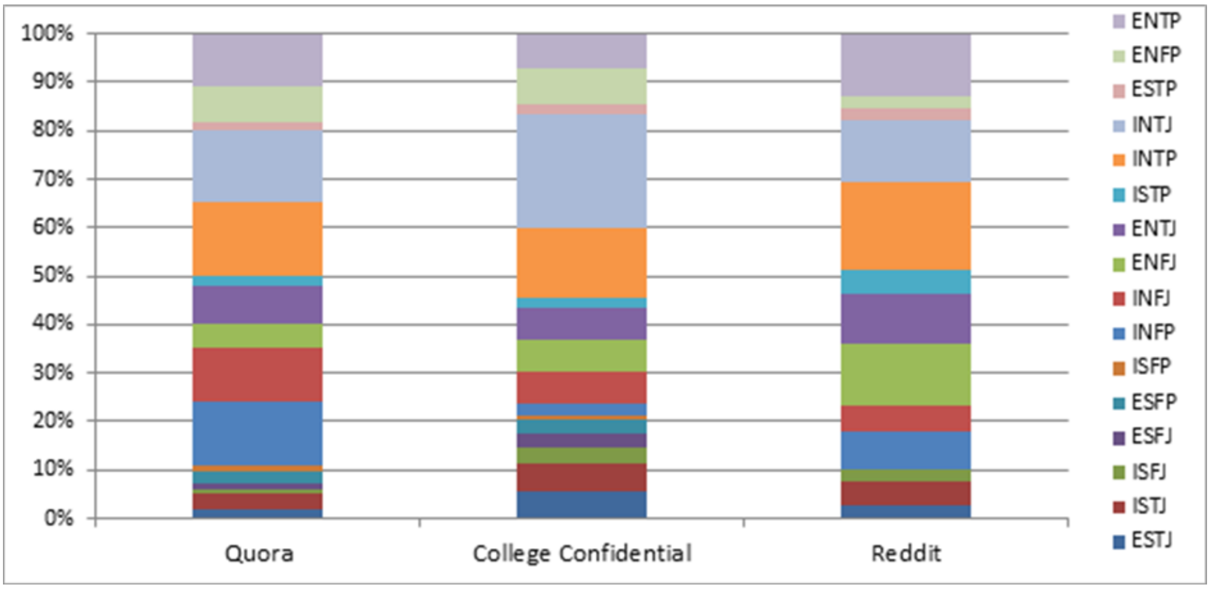

Figure 19: Distribution of MBTI types in Quora, College Confidential and Reddit

Table 8.2 Comparing the distribution of personality in three social networking websites

	Introversion	Sensing	Feeling	Perceiving
College Confidential	59%	25%	33%	40%
Reddit	56%	18%	31%	49%
Quora	62%	15%	42%	54%

Table 8.3. The estimated frequency of Personality type from http://www.myersbriggs.org

Personality	Percentage
E	49.3%
I	50.7%
S	73.3%
N	26.7%
T	40.2%
F	59.8%
J	54.1%
P	45.9%

8.4 The Relationship between Writing Style and Personality

After identifying the Quora users who reported their personalities, in the next step, we extracted the text of these users from their responses to the questions in this website. We are only interested in the English texts which are written by the users, so their non-English characters and quotes were removed. Moreover, we removed those users who did not contribute to enough answers (i.e. less than 1000 words) and consequently to enough texts. In total, 228 users were included in the final analysis, and their texts were analysed with the LIWC tool. Written texts in LIWC are processed based on LIWC tool's dictionary. Each word in the file is associated with a word category and the output data include the percentage of words captured by the dictionary. After generating the values of all the LIWC dimensions in our Quora samples, we used Pearson correlations to find relationships between personality and these dimensions. These correlations enabled us to develop a computational model that determines the personality of people from their texts.

After analysing the text of the users with the LIWC tool, we considered the LIWC dimensions for which the correlations were significant at the 0.05 level, and these variables with their correlations are presented in Table 8.4.

Table 8.4 Correlations between personality as measured by MBTI and LIWC

Personality	Correlation
Introversion	words > 6 letters (- 0.167), Dictionary words (0,153), Unique words (- 0.238), Negate (0.241), Number (0.147), Negative emotion (0.204), Anxiety (0.147), Sad (0.177), Cognitive processes (0.194), Cause (0.189), Insight (0.138), Discrepancy (0.161), Tentative (0.2), Hear (0.152), Social (0.132), Common verbs (0.135), Humans (0.133), Present tense (0.178), Inclusive (-0.166), Occupation (-0.2), School (-0.151), Job (-0.219), Music (- 0.168), Body (0.146)
Sensing	We (-0.158), Optimism (0.139), Cause (-0182), Occupation (0.145), Sports (0.141), Colon (0.173)
Feeling	words > 6 letters (- 0.191), Unique (0.165), I (0.147), Self (0.144), Effect (0.150), Positive emotion (0.185), Positive feeling (0.244), Certain (0.166), Feel (0.136), Time (0.201), Job (- 0.175), Money (- 0.181), Physical states and functions (0.244), Body (0.192), Sexual (0.215), Sleep (- 0.246), exclamation points (0.181), Other P (-0.132)
Perceiving	Assent (-0.134), Common verb (-0.180), Family (-0.145), Humans (-0.15)

As the correlations indicate, each personality type has the tendency to express or avoid certain kinds of words. For each personality, we developed a formula by adding or subtracting the independent, correlated LIWC dimensions. The formula is expressed as follows:

$$Rp = \sum_{i=1}^{80} LIWC_i * \left|Correlation_{LIWC_i}\right| * B \qquad (5.1)$$

Where Rp indicates the relative personality, B indicates whether the correlation between the LIWC dimension and the personality is significant or not. If this correlation is significant $B = 1$, otherwise $B = 0$. For example, the Perceiving type value is computed using (Assent * 0.134 + Common verb * -0.180 +Family * -0.145 + Humans * -0.15). If, for example, after analysing one of the users' texts we find that the proportion of words for Assent, Common verb, Family and Human categories are 0.16, 1.2, 0.07 and 0.52, respectively, then $Rp = 0.16 * 0.134 \mp 1.2 * 0.180 \mp 0.07 * 0.145 \mp 0.52 * 0.15 = 0.32559$. So after calculating the relative values of the personalities of each user in each of the four dimensions (Introversion, Sensing, Feeling, Perceiving), we normalized these relative values to an absolute value that is between 0 and 100. For instance, if the highest and lowest values were 78 and -32 respectively, then these were scaled to 100 and 0 respectively and 23 will be considered as 50. A detailed result is presented in Appendix B that shows the correlations between personality as measured by MBTI types and LIWC dimensions.

To validate our formula for measuring personality, our formula was cross-tested with Reddit and College Confidential data. We gathered public texts from 35 Reddit users and 135 College Confidential users who reported their MBTI personalities. As a result, we used the LIWC tool to generate all the 80 dimensions from texts of each user. Then, by using the developed formula, we predicted the personality of each user in each dimension (as this value is relative rather than absolute, we changed the scale of the value to a number between 0 and 100). After predicting the personality of users, we labelled each dimension with Y or N depending on whether it matched the real personality or not. Dividing the number of Ys by the total number of participants gives us the accuracy of the proposed model, which was 65% for Reddit and 73% for College Confidential as presented in the Table 8.5. This indicates that the presented formula can be used for prediction of personality.

Table 8.5: Validation of the proposed formula in Reddit and College Confidential

	College Confidential	**Reddit**
Accuracy	73%	65%

8.5 Applying the Model to PEPs Participants

After gaining insights about predicting the personality from texts, we employed this method to investigate the Python Enhancement Proposal (PEP) activity and the effect of teams' personalities on their behaviour with respect to the self-assembly of development teams.

Python is largely developed through the Python Enhancement Proposal (PEP) process (Van Rossum, G, 2007). A PEP is a design document that describes a new feature for Python or its processes or environment, and the developers use mailing lists as the primary forum for discussion about the language's development. Out of 363 PEPs that were developed by the end of 2015 (the dataset used for this study), 83 of them were developed by more than one person. We removed the individual works to study teams' behaviour.

We gathered texts of the members of these 83 teams from their public activities on the internet (mostly their blogs and tweets). These teams and their members are listed in Appendix C. We could have simply analysed the commits (this is a set of changes in the source code that normally includes some texts that describes the change) of these users, but we believe commits are not a rich source of texts and mainly contains some short and technical messages; and so they cannot reveal the personalities of the developers. As a result, we extracted the online texts to achieve more reliable results. We gathered texts from blogs and other online and public activities of Python developers. We only analysed teams that had enough texts available (i.e. more than 1000 words) from all the team members, which left us with 75 teams. Then we calculated the relative personality of each member based on our proposed method that is presented in Formula 5.1. These relative values were converted to an absolute value that is a number between 0 and 100. The personality of each PEP developer is presented in Appendix D.

Based on these values that represent the personality of users in four dimensions – Extraversion-Introversion (E_I), iNtuition-Sensing (N_S), Thinking-Feeling (T_F), Judging-Perceiving (J_P) – we calculated 8 new variables: TPE of E_I, TPE of N_S, TPE of T_F, TPE of J-P, TPD of E_I, TPD of N_S, TPD of T_F, TPD of J_P. Note that the TPE in each dimension of personality is equal to the average values of the personality in that dimension for all the team members. The TPD in each dimension of personality is equal to the variance of the personality in that dimension for all the team members. Then we labelled these values from "Low" to "High" as presented in Appendix D.

The "status" attribute in a PEP document represents the state of the proposal, and it is labelled as one of these categories: "draft", "accepted", "rejected", "withdrew", "active", "deferred", "replaced", and "final". Some PEPs are never finalized, so we labelled them as failed projects, otherwise they are labelled as successful projects. Those proposals that are still active and not finalized are labelled as neither a fail nor a success. This information for each team is presented in Appendix E.

The data presented here enable us to test the self-assembly model presented in Chapter 7. Using this data, in the next chapters, we run experiments and compare the team composition of these experiments with the real data in PEPs.

8.6 Conclusion

This chapter's goal is to present the dataset we have collected that will be used to demonstrate the utility of the team assembly model presented in the previous chapter. In doing, so this chapter provides a methodological construct for studying the relationship among team personalities and their text usages. In particular, this chapter has provided information about (a) the distribution of personality among social network users, (b) a computational model to determine the relationship between personality as measured by MBTI and LIWC dimensions, and (c) information about personality as measured by MBTI of teams and individuals in PEPs. In other words, in this work, a large-sized dataset from Quora enabled extensive correlations to be identified for a broad range of LIWC variables and the personality reported by users. These correlations were cross-tested with two more social networking websites: College Confidential and Reddit. The results showed the validity of our model, and we then employed this model to reveal the personalities of PEPs' developers for demonstrating our agent-based model.

Although our model for computing personality based on linguistic styles makes several contributions, from both methodological and application perspectives, there are some limitations of this approach to infer personality types and these need to be considered in the future work. These include: 1) LIWC is biased against individuals whose first language is not English, and we did not separate non-English users and developers. 2) Roles, gender, age, and other demographic factors which are not covered in this study might be involved in the linguistic styles.

In the next chapters, the data gathered in this chapter will be employed to test and validate the self-assembly model developed in Chapter 7. Moreover, in the next chapters we use this data to understand the relationship between team performance and the personalities of team composition.

CHAPTER 9

9 EXPLORING THE ROLE OF HETEROGENEITY IN TEAM PERFORMANCE USING THE PEPS DATA

This chapter tests one of the assumptions in the team-assembly model described in Chapter 7 that is about the relationship between personality and team performance, and the other assumptions will be tested in Chapter 10. This researcher believes that the categorization of tasks into either open-ended or structured may be too simplistic, and the results need more supporting evidence. However, there is sufficient relevant literature to support the hypothesis that *software development tasks can be considered open-ended and that heterogeneity of members improves the performance of development teams* (Stewart, 2006). The main focus of this chapter is exploring this hypothesis and some of the results are published in Farhangian et al., 2015c).

9.1 Heterogeneous Teams and Software Development Projects

As discussed earlier, there have been several previous general studies with respect to the significance of personality, the degree of personality diversity, and their effects on team performance. However, the results have been mixed and had conflicting conclusions (Bowers *et al.*, 2000; Day and Bedeian, 1995; Aamodt and Kimbrough, 1982; Barr *et al.*, 2011). One study found that high aggregate values of conscientiousness and openness contributed to the success of research teams (McGrath, 1986). Narrowing the focus to studies concerning personality and its diversity in the specific area of software engineering again reveals conflicting results (Andre et al., 2011; Bradley and Hebert, 1997; Miller and Yin, 2004; Peslak *et al.*, 2006; Rutherford, 2001; Lewis and Smith, 2008; Karn and Cowling, 2006). As explained in Chapter 2, some researchers believe that heterogeneity in the teams produces more creativity and consequently a better performance, while, some believe that homogeneous teams are more harmonious which is a key element for success (Stewart, 2006).

Some of these conflicting results may be due to difficulties in measuring the personalities of team members. Our model for team performance, which is presented in Chapter 7, represents a considerable simplification and its usefulness needs to be validated with real data. As mentioned earlier, generating general rules that determine the relationship between team performance and personality are not straightforward, and specific factors such as organizational issues and task structure are likely to be significant.

We assume that software development tasks, where a problem must be viewed from different perspectives and high creativity is required, can be categorized as open ended tasks. Other studies in software development teams back our hypothesis. One study has suggested that having a heterogeneous team, in terms of "Perceiving" and "Judging" personality types (B. Bradley, Klotz, Postlethwaite, & Brown, 2013) improves the efficiency of teams; since having Perceivers in teams helps the team to consider alternatives in decision making, and Judging people help the team stay on schedule. Bradley & Hebert (1997) found that successful teams had more balance between Judging types and Perceiving types (70% J, 30% P) than less successful teams with 100% Judging types. Some other studies have argued that, in general, overall diversity in personality as measured by MBTI improves the performance of software teams (Cheng, Luckett, & Schulz, 2003; Choi, Deek, & Im, 2009).

As a result, we assumed that heterogeneity (high TPD) is likely to positively affect team performance. In order to evaluate this assumption about the relationship between personality and team performance in the model which is explained in Chapter 7, tasks are assumed to be open ended. As a result, this same model presented in Chapter 7 is employed with the following formula:

$$Performance_b = Heterogeneity_{\,l} \tag{9.1}$$

Where $Heterogeneity_{\,l}$ 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 7.3.

9.2 Testing the Hypothesis about the Relationship between Personality and Team Performance

Bayesian theory (Russell & Norvig, 1995) was adopted for our computational model to predict the probability of success based on TPE and TPD in each dimension. Bayesian models are commonly used for reasoning about causes and effects in situations where information is incomplete, vague, and conflicting. Bayesian belief networks are an effective tool for predicting outcomes (deductive reasoning) or diagnosing causes (abductive reasoning). Belief networks provide mechanisms for incorporating missing and conflicting data into the calculation of results. Conditional probability explains the relationship between the states. According to Bayes' rule, P [A] is the prior probability of hypothesis A; P [B] is the prior probability of event B, and P [A|B] is the probability of A given B. P [B|A] is the probability of B given A. The Bayesian expression is expressed mathematically by Formula 9.2:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \tag{9.2}$$

In our model every task builds a naïve Bayesian network for each task. Each Bayesian network has a root node that is labeled C that determines the success (i.e. task completion) of the project, which is represented in Formula 9.3.

$$P[C|TPD\_EI, TPD\_NS, TPD\_TF, TPD\_JP, TPE\_EI, TPE\_NS, TPE\_TF, TPE\_JP] = P[C] * P[C, TPD\_EI] * [C, TPD\_NS] * [C, TPD\_TF] * [C, TPD\_JP] * [C, TPE\_EI] * [C, TPE\_NS] * [C, TPE\_TF] * [C, TPE\_JP] \tag{9.3}$$

The WEKA machine learning software tool was employed (Witten, et al., 2016) to generate and test the Naïve Bayes model on the PEPs data as described in Chapter 8. By using the NaiveBayesSimple algorithm in Weka, the probability of each condition is computed and presented in Table 9.2. Based on these probabilities, we can estimate the probability of success in each task based on team composition personality. For example, the first row (TPE_EI|C) indicates that the probability of success when TPE_EI is low (team is Extraverted) is 0.3, whereas when TPE_EI is high (team is Extraverted) the probability of success is 0.69.

Table 9.2: Team performance and personality

Probability of success in different conditions in terms of the team personality	LOW	HIGH
TPE_EI|C	0.3	0.69
TPE_NS|C	0.88	0.12
TPE_TF|C	0.19	0.81
TPE_JP|C	0.57	0.47
TPD_EI|C	0.36	0.63
TPD_NS|C	0.28	0.72
TPD_TF|C	0.3	0.7
TPD_JP|C	0.18	0.82

In all of the four dimensions, higher TPD improves the probability of team success. Concerning the TPD of the Extraverted-Introverted dimension, the probability of success is 0.63 when the team is heterogeneous, compared to a probability of success of 0.36 with a homogeneous team. In both the iNtuition-Sensing and Thinking-Feeling dimensions, we could expect a probability of success of about 0.7 with a heterogeneous team, compared to a 0.3 probability of success for a homogeneous team. The Judging-Perceiving dimension is even more sensitive regarding the diversity of team composition, and heterogeneity improves the likelihood of success from 0.18 to 0.82. Also, Table 9.2 shows that teams with higher TPE in some personality types are more successful, particularly Introverted, iNtuition, Feeling and Judging types help teams to be more successful.

These results strongly suggest that heterogeneity improves the likelihood of success in PEPs. Later, in Chapter 10, this hypothesis is tested.

9.3 Conclusion

This chapter tests one of our hypotheses in the self-assembly model in Chapter 7, which assumes that heterogeneous teams improve the efficiency of software development projects. Using data from PEPs and a Bayesian model it can be concluded that there is a strong positive relationship between a team's heterogeneity, in terms of their personalities, and its performance. These findings suggest that our team-assembly model is realistic, and its validity will be tested in Chapter 10.

As mentioned earlier, measuring performance needs some additional level of complexity, similar to the comprehensive model that is described in Chapter 3. This researcher believes that, depending on some variables such as the culture and structure of organizations and the nature of tasks, a comprehensive model needs to be developed to measure team performance. An enriched version of this model will be presented in Chapter 11 that shows the relationship between personality and team performance.

CHAPTER 10

10 DEMONSTRATING THE USABITILITY OF THE TEAM FORMATION MODEL

In Chapter 7, we developed a self-assembly model. In order to demonstrate the utility of this model, we gathered the key data in the Python Enhancement Proposals (PEPs) and also revealed the personality of the PEP's developers, as explained in Chapter 8. Chapter 9 showed that it is realistic to assume in our self-assembly model, that heterogeneity improves the efficiency of the software project teams. In this chapter, we use agent-based modeling to test a number of hypotheses on the team formation mechanism by using data from the Python Enhancement Proposal (PEP) process. In other words, by using agent-based simulations, we are able to assess the extent to which our hypotheses in Chapter 7 explain the behavioral outcomes in the PEPs data. Some of the results presented in this chapter were published in (Farhangian et al., 2016a).

10.1 Experiments and Cross Validation

The model proposed in Chapter 7 analyses two types of tasks; structured and open-ended. We assumed that software projects are open-ended and that heterogeneous teams, in terms of personality, positively influence their efficiencies. Our empirical findings in Chapter 9 have confirmed that this assumption is realistic. Therefore, we have the following formula in our model for team performance.

$$Performance_b = Heterogeneity_l \tag{10.1}$$

We use the above formula instead of Formula 7.3, because we have one type of tasks which are open-ended and positively affected by the heterogeneous teams. Apart from that, the other assumptions and formulae are similar to those described in Chapter 7 in Figure 16.

In order to evaluate our model, we used a cross-validation procedure. However, cross-validation when the data are dependent on each other is not straightforward, as in this case different periods of time cannot be studied separately. So we use a special case of K-fold cross validation. In K-fold validation, the data set is split into K parts, one part is used to train the model and the remaining K-1 parts are for testing the model. Based on suggestions made by Arlot & Celisse (2010), we used the following algorithm:

- Set the data as $y_1, \ldots, y_t$ and let the model forecast the next observation which is $\hat{y}_{t+1}$. Then compute the error ${e^*}_{t+1} = y_{t+1} - \hat{y}_{t+1}$for the forecast observation.
- Repeat step 1 for $t = m, \ldots, n-1$ where m is the minimum number of observations needed for fitting the model.
- Compute the Mean Squared Error (MSE) from ${e^*}_{m+1}$,…, ${e^*}_n$. In this case we focus on the number of correctly predicted observations.

Now we describe the pseudocode presented in Figure 20 in detail. In total, we had access to the data of 78 teams. Our simulations start with 10% of the teams (8 teams as shown in line 3 of Figure 20). Among the 78 teams, the compositions of the first 8 teams are assumed to be known (i.e. the minimum number of observations needed for fitting the model as indicated in Step 2 above), and the model predicts the composition of the remaining 70 teams. In other words, at the beginning we employ our model on the first 8 teams, and the members of these teams update their beliefs in terms of familiarity and past performances with each other. The performance of the model is then evaluated by counting the numbers of both correctly predicted teams and wrongly predicted teams (line 22). This process is iterative, and in the next iteration we select the first 9 teams in order to predict the compositions of the remaining 69 teams. Every time that we do a new iteration, we assume all of the previous tasks are completed and all of the agents are free. We continue the process in this manner until the composition of 76 teams and the compositions of the last two teams are unknown (hence the value of i was set to 76 in line 3 of Figure 21). The accuracy of the model is considered to be the average of all of these 69 iterations. Note that the last two teams (teams 77 and 78) are used to test the model developed when applying the model with 76 teams (i = 76). Furthermore, to avoid the influence and randomness of blindly assigning a member as a requestor or contributor, performances are reported as the average of 100 simulation runs of the experiment. So, in total we tested 2485 teams and each of them for100 simulations.

```
1. Data ← Dataset containing all available information for all
   participants
2.   // Set starting value, i = 8
3.  FOR i = 8 to 76
4.   Select the first i teams as known
5.   Add all features from the dataset to the tasks and employees
6.   Select the individuals from unknown remaining teams
7.   Label F (number of unknown teams) people as the requestors
8.   Label the others (80-F) as contributors
9.          IF labelled as requester
10.            Assess the contributors based on Formula 7.1
11.            IF the contributor has the minimum requirements
12.               Send the request to the contributor with the highest
   score
13.         IF Labelled as a contributor and has been invited to join a
   team
14.            If requested by a team member from a previously formed team
15.               Decide whether to join based on Formula 7.6
16.            If requested by new requestors
17.               Select the requester with the highest score based on
   formula 7.1
18.         IF a task has the required number of contributors
19.            Perform the task
20.            Update Performance (Formula 7.5)
21.            Update Familiarity (Formula 7.2)
22.      Calculate the number of correctly predicted teams
          and the number of wrongly predicted teams
23.      END FOR //(at line 3)
```

Figure 20: Team composition prediction algorithm

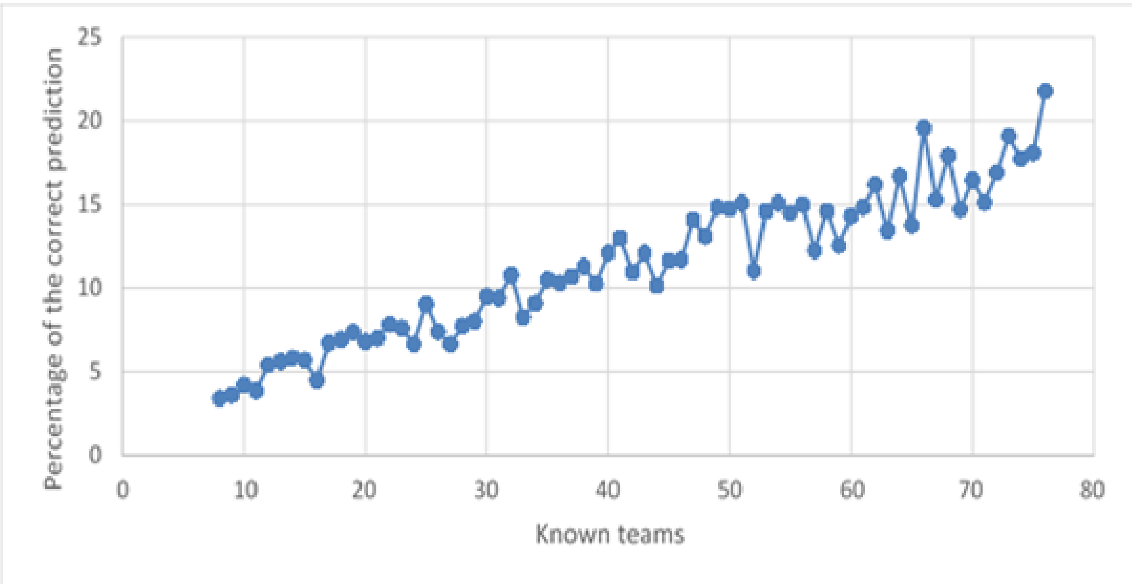

Figure 21: The performance of the model with different percentage of known teams.

Now we discuss the other steps of the algorithm. When a certain number of teams are known (based on the value of i), then the rest of the teams (F = 78 - i) need to be formed. To form those F teams, F individuals are chosen to be the requestors. The rest of the participants are considered to be contributors (lines 7 and 8). Each requestor sends invitations for others to join. First, based on his Judging / Perceiving personality (as indicated in Formula 7.6), the requestor sends requests to the teammates from the last formed PEPs team. If one or more refuse to join, then the requestor sends the invitations to the other members. Upon receiving responses, the requestor assesses which contributor should be selected based on Formula 7.1. Upon receiving the requests, the contributor can decide which team to join. There are two cases here. If the request comes from a team member with whom the contributor has worked in the past, the decision to join is reached based on Formula 7.6 (lines 14-15). If the request comes from new requestors then the decision is based on Formula 7.1 where the contributor selects the requestor who has the potential for the best performance (lines 16-17). A contributor upon receiving the request will evaluate which team to join, inasmuch as it may have received multiple requests (lines 14-16). Once the criteria for forming a team are met, the team performance for the task, and the scores for performance and familiarity are updated (lines 18-21). Note that we assume that team members work on one PEPs project at a time. Also, the simulation proceeds to the next iteration once the work for a PEPs project is complete and all contributors are available to be invited for the next project.

As explained in the pseudocode (lines 5-8), the number of tasks and the number of contributors required for each task in our simulation are known a priori, which is the same as for the original PEPs team.

Figure 21 shows simulations results of a scenario where we varied the number of teams whose compositions are known (starting with 8 teams on the x-axis). The y-axis shows the number of teams that were correctly predicted by the model. We can see that by increasing the number of known teams, the accuracy of prediction increases (from less than 5% when only 8 other teams' compositions are known to over 20% when the composition for 76 teams are known). Now we discuss the initial values assigned for the six factors considered in the model. These factors are summarized as follows:

- The effect of ***familiarity*** on the teammate selection.
  We assume being familiar with other teammates improves the likelihood of being chosen for the future teams.

- The effect of ***past performance*** on the teammate selection.
  We assume being successful or unsuccessful plays an important role in the future team selection.
- The effect of ***Feeling personality*** (T-F) on the familiarity.
  Familiarity is assumed to relate to Feeling-Thinking personality dimension and for those with a Feeling personality, familiarity with the other teammates is more important as compared to those with a Thinking personality.
- The effect of ***Sensing personality*** (N-S) on the past performance.
  Past performance is assumed to relate to a Sensing personality, and those with Sensing personalities put more weight on past performance when they choose a teammate.
- The effect of ***Extraverted personality*** (E-I) on the connections.
  Having more connection means being more familiar. This connection is assumed to be positively impacted by Extraverted personality.
- The effect of ***Perceiving personality*** (J-P) on leaving a team.
  It is assumed that team members with Perceiving personalities change their teams and experience new teams more often than team members with a Judging personality, and vice versa.

We can think of the individuals as nodes in a network that are connected to each other by links. One of the links represents the familiarity and another one represents previous performance. The strength of the links increases if their familiarity over time increases and if the previous performance increases. We set the initial thresholds for familiarity and previous performance (representing minimum requirements for interaction), which are 0 for previous performance and 0 for familiarity. In addition, each individual has 4 randomly assigned values for his/her personality that represent their overall personality as measured by MBTI.

We have experimentally examined the performance of our proposed model, and on average we predicted 8.3% of the teams (which is 207 out of 2485 teams) correctly. When the proposed model is not employed and we ask the requestors and the contributors to randomly select each other, the correctly predicted team occurs only 2.8% of the time (which is 70 out of 2485 teams) on average. This suggests that personality is a factor in this domain. As we discussed above, this is a minimal model that only focusses on features related to personality.

The model's overall performance could be improved by considering additional significant characteristics, such as required technical skills for the task, however we wanted to concentrate here just on the personality dimension (i.e. not dilute the model with other influencing characteristics) and how it affects collective interactions.

Furthermore, we tested the extent to which each of six model parameters influence the final results (prediction of which teams are likely to be formed in the future). The six factors in our model, which were discussed in Chapter 7, are given below:

- the effect of ***familiarity*** on the teammate selection (Formulae 7.1).
- the effect of ***past performance*** on the teammate selection (Formula 7.1).
- the effect of ***Feeling personality*** (T-F) on the familiarity (Formula 7.2).
- the effect of ***Sensing personality*** (N-S) on the past performance (Formula 7.1).
- the effect of ***Extraverted personality*** (E-I) on the connections (Formula 7.2).
- the effect of ***Perceiving personality*** (J-P) on the team changing (Formula 7.6).

Each of these factors either affects (represented by the value of 1) or does not affect (represented by the value of 0) the team formation, which results in $2^6 = 64$ possible conditions. Whenever we turn off a variable (set it to a value of 0), it means that all the agents behave similarly with respect to that particular variable. Each condition was examined via a separate experiment, and each of these experiments was repeated 100 times. These results are presented in Table 10.1, where the average percentage of true predictions of teams' combinations is shown in the last column on the right.

Table 10.1: The average effect of variables on the model's performance

Combination	Feeling (T-F)	Perceiving (J-P)	Extraverted (E-I)	Familiarity	Previous performance	Sensing (N-S)	Score (in percentage)
1	1	1	0	1	1	0	10.96
2	1	1	0	1	1	1	10.42
3	1	1	1	1	1	0	9.51
4	1	0	1	1	1	0	9.17
5	1	1	1	1	1	1	8.91
6	0	1	1	1	0	0	8.68
7	0	1	0	1	1	0	8.66
8	1	0	1	1	1	1	8.56
9	1	1	1	1	0	0	8.46
10	0	1	0	1	1	1	8.46
11	1	1	0	1	0	1	8.42
12	0	1	1	1	1	0	8.24
13	1	0	0	0	1	0	8.06
14	0	1	0	0	1	0	8.01
15	0	1	1	1	1	1	7.99
16	1	1	1	0	1	1	7.96
17	1	0	0	1	1	1	7.87
18	0	1	0	0	1	1	7.84
19	1	0	0	1	0	1	7.82
20	1	1	1	1	0	1	7.80

21	1	1	0	0	1	1	7.78
22	1	0	1	0	1	0	7.73
23	0	1	1	1	0	1	7.69
24	1	1	0	0	0	1	7.64
25	0	1	0	1	0	1	7.53
26	0	1	1	0	1	1	7.41
27	1	0	0	1	1	0	7.4
28	0	0	0	1	0	0	7.31
29	1	1	1	0	0	1	7.31
30	0	0	1	1	1	1	7.3
31	0	0	0	1	1	1	7.18
32	0	1	0	1	0	0	7.16
33	0	0	1	0	1	0	7.15
34	1	0	1	1	0	0	7.04
35	0	1	0	0	0	0	7.01
36	1	0	1	0	1	1	7.00
37	1	0	1	1	0	1	7.00
38	1	1	0	1	0	0	6.85
39	0	0	1	0	0	1	6.78
40	0	0	1	1	1	0	6.74
41	1	1	0	0	1	0	6.67
42	1	1	1	0	1	0	6.65
43	1	0	0	0	1	1	6.5

44	0	0	0	0	1	0	6.44
45	0	0	0	1	1	0	6.38
46	1	1	1	0	0	0	6.33
47	0	0	1	0	1	1	6.21
48	0	0	1	1	0	1	6.09
49	1	0	0	1	0	0	5.99
50	1	1	0	0	0	0	5.93
51	0	1	1	0	1	0	5.8
52	1	0	1	0	0	0	5.41
53	0	0	0	0	1	1	5.23
54	0	0	1	1	0	0	5.19
55	0	1	0	0	0	1	4.71
56	1	0	0	0	0	1	4.69
57	0	1	1	0	0	1	4.58
58	0	1	1	0	0	0	4.44
59	1	0	0	0	0	0	4.22
60	0	0	0	1	0	1	2.92
61	0	0	0	0	0	0	2.87
62	0	0	1	0	0	0	2.73
63	1	0	1	0	0	1	2.06
64	0	0	0	0	0	1	2.01

Note that when all the six columns have 0, the average correct prediction is 2.87%, and when all the six columns have six 1's the average value is 8.9% (based on results shown in the last column of Table 10.1). Note that the best scores are obtained when the values of a majority of the variables are turned on (see rows 2 to 6 of Table 10.1). This implies that some variables in the model are more important than the others, which is an issue that is further scrutinized below.

Once we measured the performance of the different factor combinations as shown in Table 10.1, we used the Pearson correlation measure to see which variables were correlated to the model's performance (score shown in the last column in Table 10.1). The correlation results presented in Table 10.2 show four factors that are significantly correlated with performance:

- Previous Performance
- Familiarity
- Feeling
- Perceiving

Table 10.2: Correlations between the model's performance and the variables

		Score
Feeling	Pearson Correlation	.283*
	Sig. (2-tailed)	0.024
	N	64
Perceiving	Pearson Correlation	.340**
	Sig. (2-tailed)	0.006
	N	64
Extroverted	Pearson Correlation	0.004
	Sig. (2-tailed)	0.975
	N	64
Familiarity	Pearson Correlation	.506**
	Sig. (2-tailed)	0.000
	N	64
Previous performance	Pearson Correlation	.433**
	Sig. (2-tailed)	0.000
	N	64
Sensing	Pearson Correlation	0.083
	Sig. (2-tailed)	0.515
	N	64

Significant level, * - $p < 0.05$ and ** - $p < 0.1$

Familiarity was the factor with the highest Pearson correlation of 0.506, followed by Previous Performance, Perceiving, and Feeling. All of these factors are significant at the $p < 0.05$ level. Thus the influence of Extraversion on the number of connections an individual has and the Sensing-influenced consideration of previous performance did not improve the accuracy of the model for this particular application. Considering these results, we then simplified our previous model by excluding the roles of Extraverted and Sensing personality type influences. The final model uses the same formula for performance and heterogeneity as described in Formulae 7.4 and 7.5, respectively. However, the formulae to evaluate contributor performance (Formula 7.1) and familiarity (Formula 7.2) needed to be adjusted, since Formula 7.1 considers the iNtuition-Sensing dimension and Formula 7.2 considers the Extraversion-Introversion personality dimension.

As mentioned in connection with the assumptions, past-success would be a more important factor for people with Sensing personalities, and familiarity would be a more important factor for people with Feeling personalities. In our original model, people find a team member based on Formula 7.1 for which both familiarity and performance had the same weight. To examine this further, we chose to consider a variable weighting of those two factors by employing weights α and β as shown in Formula 10.2. So requester j offers C_{ji} to the contributor i as presented in Formula 10.2, which is the modified version of Formula 7.1, where the effect of the iNtuition-Sensing personality dimension has been eliminated.

$$C_{ji} = \frac{\left((v_{ji} * \alpha) + (TF_j * familiarity_{ji} * \beta\,)\right)}{100 + TF_j} \tag{10.2}$$

We took into account the weight from the correlation results shown in Table 10.2 for measuring the relative importance of familiarity and performance variables in Formula 10.2. The correlation for familiarity was 0.506, and the correlation for previous performance was 0.433 (see Table 10.2). In order to measure their relative importance, we assigned the weight for familiarity to be 0.506 / (0.506 + 0.433) = 0.534 and the weight for the past performances to be 0.433 / (0506 + 0.433) = 0.46. So, we have the following formula:

$$C_{ji} = \frac{\left((v_{ji} * 0.46) + (TF_j * familiarity_{ji} * 0.534\,)\right)}{100 + TF_j} \tag{10.3}$$

Given the observed insignificance of Extraversion, we modified Formula 7.5 accordingly. If an agent is a part of a team with another agent, its familiarity increases. The familiarity of agent j with agent i is calculated using Formula 10.4, where the effect of the Extraversion (the E-I personality dimension) has been dropped in this formula.

$$familiarity_{ji}(t) = familiarity_{ji}(t-1) + 1 \tag{10.4}$$

Moreover, in our previous simulations, we effectively set thresholds for familiarity and previous performance, which were 0. We investigated whether a higher threshold is required for previous performance and familiarity to make them effective. There is no study in the literature to help determine this threshold; so we conducted new simulation-based experiments that took various thresholds for familiarity, from a value of 1 (where agents had one interaction before) up to 10. Also, and along similar lines, we varied the threshold for previous performance from 1 to 10. Results over an average of 1000 simulations are presented in Figure 22.

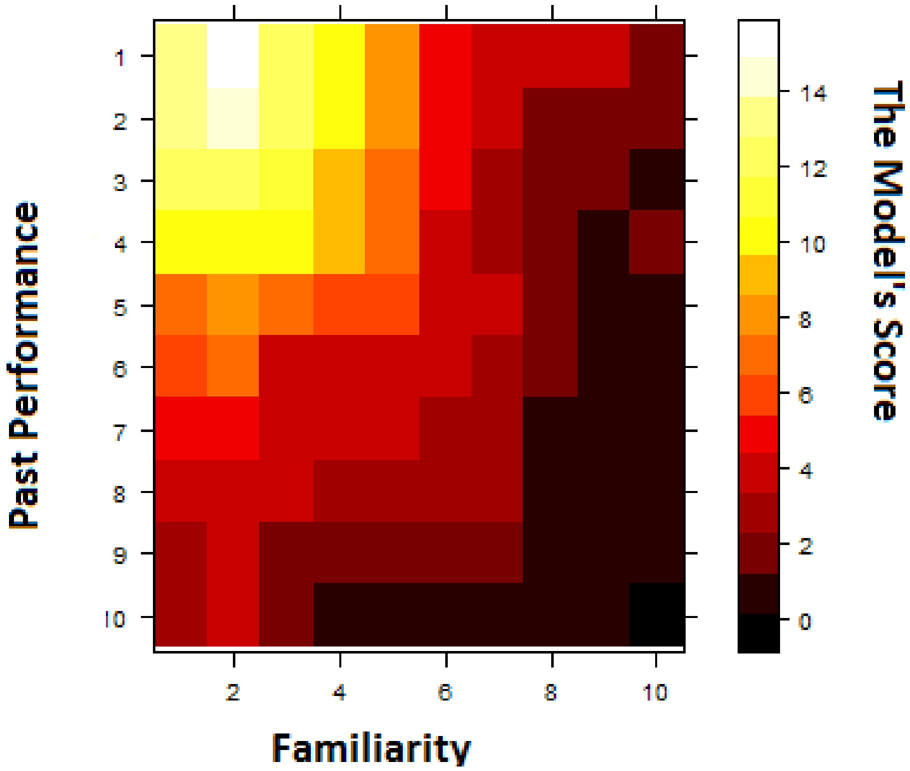

Figure 22: The model's performance and thresholds for familiarity and performance

Figure 22 shows the model's performance with respect to familiarity (represented along the x-axis) and past performance (represented along the y-axis). The cell colouring in the figure represents the model's score for a particular combination of *X* and *Y* values from light to dark (white representing the best results obtained and black representing the worst results). As can be seen in Figure 22, by evaluating various values of the parameters in our model, we could improve the accuracy of our model by up to 14.9%. The best performing model took the value 1 for past performance and 2 for familiarity. The results show that more than one interaction is required to make people sufficiently familiar with each other. Thus setting a threshold of two for familiarity improves the accuracy of a model. However, it was discovered that people trust the ability of their team members if they are successful, even if the experience was only in one project (i.e. past performance value of 1).

10.2 Conclusion

This chapter contributed to the relatively unexplored area of using simulation in modeling personality and team formation in temporary teams. We used a social agent-based model that was developed in Chapter 7 to explore how different variables, including personality, explain team formation mechanism in PEPs.

First, we found a combination of some social hypotheses which helped us to correctly predict the formation of some teams in PEPs. This highlights the potential of simulation for understanding team formation. We compared the results of different combinations of our hypotheses to examine their reliability. Our results indicate that some factors do not matter in team formation in PEPs. However, we have found that four main factors determine the accuracy of our model. These are the Perceiving personality which affects the probability of changing teams, the familiarity which affects team formation, the Feeling personality which affects familiarity, and the previous success which affects team formation.

In this work, we showed that this model predicted 8.3% of teams successfully when compared to a model that guesses at random, which predicted team compositions correctly only 2.8% of the time. We were able to refine the model based on statistical results. Based on the correlation results obtained (using the factors that were significant at the level of $p < 0.05$), we developed a new model that excludes two statistically insignificant factors (Extraversion and Sensing personality). To consider the relative importance of familiarity versus previous performance, we weighted these factors by their correlations. Also, the threshold requirements for familiarity and previous performance needed to be revisited. These were investigated by running the models with various values (using parameter sweeping) for these two variables, and we obtained results as shown in Figure 21. The results indicate that the accuracy of our new model increased to 14.9% for a certain combination of values for these two variables. We note that these prediction results were obtained using an agent-based simulation, which highlights the utility of the modelling approach in understanding team formation.

These results are particularly relevant for addressing the organizational issue of planning for ad hoc team formation in domains such as open source software development (OSSD). There is an increasing interest among both practitioner and researcher communities in investigating the success and failure of OSSD teams, in particular, due to its open nature that may attract incompatible personality types. Traditionally, well-known factors such as skills, knowledge and capability of employees were considered while forming teams (Barrick, et al., 1998). However, the role of personality has been less scrutinized in detail as compared to the other factors. Possible reasons for this could include the unreliability and subjectivity involved in assessing an individual's personality and the short turnaround time associated with performing tasks as a project group. Our model addresses this issue by inferring the personality automatically from written text.

More importantly, our model has provided some initial evidence about the role of personality in affecting team formation, which shows that considering the personality (alone) in the model, can improve successful future team prediction by about 15%. Though small, the model's predictive power highlights the influence of personality types on ad hoc team formation.

CHAPTER 11

11 RELATIONSHIP BETWEEN PERSONALITY AND TEAM PERFORMANCE IN PEPS

Throughout this thesis, some assumptions have been made about the relationship between team personality and team performance. In Chapter 9, we explored one of our arguments that hypothesized that heterogeneity produces more successful results. However, in order to have more in-depth analysis, a data-driven approach is introduced in this chapter that can be applied in organizations with different structures and task natures. This chapter presents a decision-support model that can assist software team managers to form teams that are likely to have appropriate personality combinations of team members. We used the PEPs data and employed association rule mining to find the best rules to explain the relationships between team performance and personality. Some of the results presented in this chapter are accepted in (Farhangian et al, 2016b).

11.1 Relationship between Personality and Team Performance

Finding some interesting rules that show the relationship between personality and team performance should go beyond the oversimplification of categorization of tasks into open-ended and structured. Using these rules can improve the modeling of team formation. However, there is no global formula for determining the relationship between personality and team composition, and many factors such as the structure of tasks and the nature of the organizations should be taken into consideration. As a result, we introduce a data-driven approach that should be used to extract customised rules for each company.

In this connection, we applied the Apriori algorithm (Agrawal & Srikant, 1994), which is used for mining association rules. Here we identify the association rules between personality dimensions (e.g. TPE_EI) and team performance (i.e. success of a PEP). Apriori uses breadth-first search and a tree structure to count candidate item sets efficiently. Association rule-mining employs the following metrics:

- ***Support*** indicates the frequency of the rule within a database, and a high value means that the rule is commonly followed (with the maximum value of 1 showing every team following the rule).
- ***Confidence*** indicates the percentage of rules containing the antecedent that also contains the consequent. For example if a rule is {butter, bread} → Milk and its confidence is 100% it means that 100% of the times a customer buys butter and bread, milk is bought as well.
- ***Lift*** indicates the ratio of the probability of an event occurring under a new condition, to the probability of an event occurring under an old condition. The value of lift is that it considers both the confidence of the rule and the overall data set.

The analysis was conducted with the support threshold setting at 0.08 and 0.7 as the confidence level similar to work of Agrawal & Srikant, 1994. This means each candidate with support greater than 0.08 and with a confidence level over 0.7 is considered a candidate with strong association rules.

Table 11.1 shows a group of useful rules for managers so they can make decisions about which compositions would affect the team performance. As an example, the first recommended rule is as follows:

TPE_EI=HIGH & TPD_JP= HIGH ➔ Success

Support for this rule is 0.13, which shows the frequency of our rule in the database. Our confidence is 100%, which shows the percentage of times that rule has been found to be true. Lift is 2.08, which indicates that the antecedent and consequent are dependent on each other. In other words, it indicates that the antecedent improves the probability of having a successful performance by 2.08 times. Generally, the rule shows that teams with highly Introverted personalities, and which are heterogeneous in the Judging and Perceiving dimension, are more successful. Also, the following definitions for personality dimensions are required to understand the results presented in Table 11.1:

- TPE_EI: High means the team is Introverted, low means the team is Extraverted.
- TPE_TF: High means the team is Feeling, and low means the team is Thinking.
- TPE_JP: High means the team is Perceiving, and low means the team is Judging.

- TPE_NS: High means the team is Sensing, and low means the team is iNtuition.

11.2 Important Findings

In this section, we present the important findings from Table 11.1. Some rules such as Rule 6 suggest that we need heterogeneous teams in the iNtuitive-Sensing dimension. Heterogeneity in the iNtuition-Sensing personality results in successful group performance, since Sensing types bring facts and details and iNtuitive types provide new possibilities and ideas. This finding is confirmed in a study by Choi et al., (2008). They found that diverse sensing and intuition preferences would challenge each other and offer a wider array of solutions. Also, they considered the different make up of pair programmers. In their studies the most successful teams were diverse teams who are neither totally opposite (e.g. TN-FS) nor alike (e.g. TS-TS). One of the successful pairs was ST-NT, and based on that pairing they concluded that similarities in the Thinking-Feeling dimensions provide common ground for reconciling differences, while diversity in the iNtuition-Sensing dimension helps teams to generate new ideas. In their study, when comparing opposite teams (i.e. teams with opposite personalities) to alike teams, opposite teams were more successful.

Table 11.1: Selected strong association rules

Rules' Number	Antecedent	Consequent	Support	Confidence	Lift
1	TPE_EI=HIGH & TPD_JP= HIGH	Success	0.13	1	2.08
2	TPE_EI=LOW & TPE_TF=LOW	Fail	0.106	1	3.57
3	TPE_EI=HIGH &TPE_TF=HIGH &TPE_JP=LOW	Success	0.106	1	2.08
4	TPE_EI=HIGH & TPE_TF=HIGH& TPD_JP= HIGH	Success	0.106	1	2.08
5	TPE_EI=HIGH & TPE_JP=LOW	Success	0.146	0.92	1.91
6	TPE_JP=LOW & TPD_NS=HIGH	Success	0.146	0.92	1.91
7	TPE_NS=LOW & TPE_TF=HIGH	Success	0.133	0.91	1.89

	&TPE_JP=LOW				
8	TPE_EI=HIGH & TPD_NS=HIGH & TPD_JP=HIGH	Fail	0.12	0.9	3.21
9	TPE_EI=HIGH & TPD_NS=HIGH &TPD_JP=HIGH	Success	0.12	0.9	1.87
10	TPE_F=HIGH & TPE_JP=LOW &TPD_NS=HIGH	Success	0.12	0.9	1.87
11	TPE_JP=LOW &TPD_TF=HIGH	Success	0.106	0.89	1.85
12	TPE_EI=HIGH &TPE_NS=LOW& TPE_JP=LOW	Success	0.106	0.89	1.85
13	TPE_NS=LOW &TPE_JP=LOW & TPD_NS=HIGH	Success	0.106	0.89	1.85
14	TPE_NS=LOW &TPE_JP=LOW	Success	0.173	0.87	1.81
15	TPE_TF=HIGH & TPE_JP=LOW	Success	0.16	0.86	1.78
16	TPE_EI=HIGH &TPE_TF=HIGH &TPD_NS=HIGH	Success	0.146	0.85	1.76
17	TPE_NS=LOW & TPD_NS=HIGH & TPD_JP=HIGH	Success	0.146	0.85	1.76
18	TPE_TF=HIGH &TPD_NS=HIGH & TPD_JP=HIGH	Success	0.146	0.85	1.76
19	TPE_JP=LOW	Success	0.21	0.84	1.74
20	TPE_EI=HIGH & TPD_NS=HIGH	Success	0.2	0.83	1.72
21	TPE_EI=HIGH & TPE_NS=LOW & TPD_NS=HIGH	Success	0.133	0.83	1.72

22	TPE_NS=LOW & TPE_TF=HIGH & TPD_NS=HIGH & TPD_JP=HIGH	Success	0.133	0.83	1.72
23	TPE_TF=LOW & TPE_JP=HIGH	Fail	0.12	0.82	2.92
24	TPD_EI=LOW & TPD_NS=HIGH	Success	0.12	0.82	1.7
25	TPE_NS=LOW &TPD_JP= HIGH	Success	0.106	0.8	1.66
26	TPE_JP=LOW &TPD_JP= HIGH	Success	0.106	0.8	1.66
27	TPE_EI=HIGH & TPD_EI=HIGH & TPD_NS=HIGH 10	Success	0.106	0.8	1.66
28	TPE_TF=HIGH &TPD_EI=HIGH &TPD_NS=HIGH	Success	0.106	0.8	1.66
29	TPE_EI=HIGH &TPE_NS=LOW &TPE_TF=HIGH &TPD_NS=HIGH	Success	0.106	0.8	1.66
30	TPD_JP= HIGH	Success	0.146	0.79	1.64
31	TPE_NS=LOW &TPD_NS=HIGH	Success	0.22	0.77	1.6
32	TPD_NS=HIGH &TPD_JP=HIGH	Success	0.17	0.76	1.58
33	TPE_TF=HIGH & TPD_NS=HIGH	Success	0.24	0.75	1.56
34	TPE_TF=HIGH & TPD_JP=HIGH	Success	0.2	0.75	1.56
35	TPE_NS=LOW & TPE_TF=HIGH &TPD_NS=HIGH	Success	0.186	0.74	1.54
36	TPE_EI=HIGH &TPE_TF=HIGH &TPD_EI=HIGH	Success	0.146	0.73	1.52
37	TPE_TF=HIGH &TPD_JP= HIGH	Success	0.106	0.73	1.52
38	TPE_EI=HIGH &TPE_TF=HIGH &TPD_JP=HIGH	Success	0.106	0.73	1.52

39	TPE_NS=LOW &TPD_TF=LOW &TPD_JP=HIGH	Success	0.106	0.73	1.52
40	TPE_TF=HIGH &TPD_EI=HIGH &TPD_JP=HIGH	Success	0.106	0.73	1.52
41	TPE_NS=LOW &TPE_TF=HIGH & TPD_JP=HIGH	Success	0.173	0.72	1.5
42	TPD_NS=HIGH 32	Success	0.306	0.72	1.5
43	TPE_EI=HIGH &TPD_JP=HIGH	Success	0.16	0.71	1.48

Some rules, such as Rule 3, suggest that in conjunction with heterogeneity in terms of iNtuition-Sensing, having generally high Judging in teams is beneficial. They suggest that low Perceiving leads to better team performance; in other words, having a Judging personality has a positive influence on team effectiveness. This finding is consistent with another study about the relationship between personality as measured by MBTI and software development teams, which suggests that Judging personality involves dealing with the external world and meeting deadlines (Gorla & Lam, 2004). In the Five Factor Model (FFM), Judging is correlated with Conscientiousness (McCrae & Costa, 1989), however, this correlation is not very strong. The positive relationship between Conscientiousness and team performance has been shown by several researchers, such as English, Griffith, & Steelman (2004). Concerning this connection, Cheng et al.(2003) showed that diverse pairs in iNtuition and Sensing performed significantly better than homogeneous Sensing type pairs, but not better than iNtuition type pairs (Cheng, Luckett, & Schulz, 2003). iNtuition in MBTI is related to Openness to experience in FFM (McCrae & Costa, 1989), and several studies have confirmed the positive role of Openness in team performance (e.g. Neuman et al., (1999), Bradley, Klotz, Postlethwaite, & Brown, (2013)).

Another pattern that can be seen in the rules (for example rules 15 and 23) is that a Feeling personality improves the efficiency of teams. We can speculate that Feeling types may focus on the harmony of teams, while Thinking types may prefer to focus on getting the job done, and that these two types might frustrate each other. Bradley et al. (1997) studied and compared two teams of software developers. The successful team had a larger percentage of Feeling types. They concluded that Feeling personalities helped teams to focus more on group harmony, and consequently to engender successful performance. These findings are in line with our findings with the PEPs-based data that High TPE in Feeling can help teams to be more successful. Also, if Feeling is to be considered similar to FFM Agreeableness (McCrae & Costa, 1989), there is even more evidence to support this finding (e.g. (Barrick & Stewart, 1998).

Some rules such as 28 and 36 suggest that a heterogeneous team in the Extraverted-Introverted dimension leads to successful performance. A variety of team members in terms of Extraversion has some benefits for teams, since Extraverted members improve communication among team members, whereas Introverted members provide internal reflection on group discussions (Bradley & Hebert, 1997).

Some of our rules, such as 9 and 12, suggest that the most successful team generally is Introverted. In contrast to our findings, several studies suggested that Extraversion improves the efficiency of software teams, such as studies by Barrick & Mount, (1991) and Barry & Stewart, (1997a). An explanation for our different results might be the different communication types in our study, as compared to the types in the studies in the relevant literature. These researchers studied organizations and teams who had oral communications, but in our case, personalities were inferred through written communication. Behaviours of Extraverted and Introverted people are highly related to the type of communication employed, and it seems that Introverted people might overcome the issue of a lack of communication when they use the textual (i.e. written) mode of communication.

In addition, in these rules, heterogeneity in terms of Judging and Perceiving personalities is a positive factor as presented in some rules such as 39 and 40, since having Perceivers in a team helps the team to consider alternatives in decision making, and Judging people help the team to be on schedule. These findings were confirmed where experiments showed that a successful team had a better balance of Judging types and Perceiving types (70% J, 30% P), whereas the less successful teams had 100% Judging types. However, if we consider Judging in MBTI to be similar to Conscientiousness in FFM, the results are conflicting. While some studies (e.g. Humphrey & Hollenbeck, 2007) showed that homogeneity in terms of Conscientiousness negatively affects performance, some others showed that heterogeneity in terms of Conscientiousness was not significantly related to overall performance (e.g. (Mohammed & Angell, 2003 and Prewett & Walvoord, 2009).

Some of the rules provide useful information, yet some of them can be difficult to interpret and conflicting with rules that managers should consult other rules and recommendations to confirm their interpretations. For instance, although low TPE in N-S leads to unsuccessful results in Rule 5, it might be because the team had low TPD in this dimension, and low TPE in N-S is not repeated in the other rules. Generally, we can see that some factors such as homogeneity in N-S, and heterogeneity in T-F, lead to poor performance, while some factors such as being Introverted and heterogeneous in J-P lead to positive performance.

11.2 Conclusion

This chapter provides a methodological construct for studying and managing the relationship between team personalities and performance. We employed our PEPs-based data set and our computational model results to determine the relationship between personality as measured by MBTI and the LIWC dimensions. Then an association rule mining algorithm was used to extract knowledge about the relationships between teams' performances and their personality as measured by MBTI profiles. Using Python software development projects (PEPs) helped us to refine our assumptions, and these give insights into the effect of personality on team performance. However, we want to stress that our general approach can be used to derive a new rule set that is customized for a specific software engineering context (say in another open source project). Most of our findings are supported by some empirical studies in the literature.

In addition to the positive role of heterogeneity in team performance, the findings of this study suggest that more emphasis should be placed on heterogeneity in terms of the cognitive style (iNtuition-Sensing dimension) and life approach (Judging-Perceiving) dimensions. Moreover, our rules suggest that the Introverted, Judging, Feeling and iNtuition-oriented temperaments improve the efficiency of teams.

CHAPTER 12

12 DISCUSSION AND CONCLUSION

This chapter summarises the major findings and how they contribute to new knowledge in teamwork modelling. The research questions of this thesis are answered, limitations of this research are discussed, and future research directions and implications are presented.

12.1 Thesis Summary

In many cases, team performance is significantly influenced by the makeup of participants' personalities and temperaments, and such scrutiny of performance must go beyond consideration of just the individual skills. Also, teamwork modelling is not only about team performance. In order to have a comprehensive understanding of teams, understanding the mechanisms behind the formation of teams is also important. The predictive capability of agent-based simulation has enabled the investigation of the team of autonomous agents, and particularly the examination of the effect of personality on self-assembly behaviour in temporary teams. The rest of this section presents a summary of the various chapters of this thesis.

12.1.1 Chapter 2

Chapter 2 consisted of three main parts. Firstly, literature in the area of teams and the impact of personality on team behaviour was reviewed. Agent-based modelling paradigms are suitable for studying the autonomous self-assembly of teams. So, the second part of Chapter 2 discussed how agent-based modelling can be used to analyse team behaviour, particularly team formation performance of self-assembly teams. The literature review presented in Chapter 2 revealed that self-assembly is a common phenomenon in teams, yet most researchers have failed to consider this dynamic behaviour. In order to reflect the real world of teamwork, self-assembly processes must be included in the model. In order to validate our model, relating personality to linguistic style was needed. So, the third part of Chapter 2 reviewed the literature about this relationship.

12.1.2 Chapter 3

In Chapter 3, in order to demonstrate the effect of the team formation mechanisms on team performance in an environment in which employees are assigned to the tasks by the manager, we developed a model for the software development industry. In this connection, by reviewing previous findings from MBTI and Belbin Team Roles, we developed a computational model to measure the personality effect on the performance of teams. In our experiments, we compared two team-formation mechanisms and their effects on the team performance in a dynamic environment. These two mechanisms are called *minimizing under competency* and *minimizing over competency*. The managers who favour the first strategy guarantee that the team has enough capacity to perform the tasks. The managers who prefer the second strategy seek to guarantee that they have enough available and competent employees for forthcoming tasks.

In the experiments, it was argued that the strategies that managers employ for allocating staff to a team are key factors for team performance. The experiments revealed that by increasing the likelihood of changes in the task requirements, the performance became poor. In the beginning, when the dynamic level of tasks is not significant, the under-competency mechanism outperformed the over-competency mechanism. However, when increases were made in the dynamic level of tasks, the over-competency mechanism ended up with a better performance compared to the under-competency mechanism. As a result, we developed a model that can help managers to choose a task allocation strategy by taking into account the dynamism level of the environment.

Moreover, in order to understand how the personalities of employees mattered in our experiments, we examined the performances of members with different distributions of personality. In other words, we analysed whether a task allocation mechanism has any advantages over another one for a particular personality distribution. Different scenarios were set, each of which represented a particular distribution of personality as measured by MBTI among the employees. In most of the scenarios, the probability of having a better performance with the under-competency mechanism was slightly better than the other task allocation mechanism. However, it was observed in some scenarios that the over-competency mechanism outperformed the under-competency mechanism.

12.1.3 Chapter 4

In Chapter 4, we developed another model that demonstrated the effect of team formation on team assembly. In this chapter we chose a model that the knowledge and skills of team members are the crucial elements for team selection and teams were partly self-assembly. We investigated how the team-formation mechanism affects the collaborative learning, and consequently the team performance, of the self-assembly teams. To do that, a modifiable template was developed for the examination of dynamic knowledge and skill influences on individual and team performance via simulation experiments. During the simulations, agents exchanged their knowledge with teammates and updated their trust concerning the knowledge of other agents. Also, they improved their skills by observing and imitating their teammates' behaviours.

Two team-formation mechanisms were compared: one based on trust (knowledge credibility) and the other one based on skill. In the first scenario, employees formed a team based on their trust or knowledge credibility towards other agents. In the second scenario, agents were assigned to a task based on their competency.

The simulation results showed that the gap between the two mechanisms' results shrank over time, and that overall, the average performance of teams formed based on the skill-based mechanism outperformed the average performance of teams formed based on the credibility-based mechanism. In contrast, the average knowledge in the teams which were based on knowledge credibility was higher than that knowledge of the teams based on skill. Moreover, it was observed that the skill growth in teams with the skill-based formation was faster than the skill growth in the credibility-based team formation scenario.

By conducting some experiments over different scenarios with different personality distributions, a relationship was observed between the personalities of employees and the overall performance. For example, it was observed that a balance of Introverts and Extraverts ended up with a better performance compared to a scenario in which all members were extremely Extraverted.

12.1.4 Chapter 5

The third model on the area of the effect of team formation mechanism on team performance was built in a game environment in which personality determined the strategy of agents in team formation and team formation was completely self-assembly. We analyzed the performance of all the possible combinations of personalities for two types of tasks (which were either open-ended or structured) and we conclude that the type of tasks can be an indicator in the team performance.

12.1.5 Chapter 6

Chapter 6 summarised the preceding three chapters (i.e. Chapters 3, 4 and 5) and argued that a thorough analysis of team behaviour was highly dependent on understanding two factors; *self-assembly team formation* and *team performance*. The general team performance has received considerable attention, but, self-assembly team formation has not been fully studied and is not well understood. This chapter argued that the understanding of teams cannot be complete without analysing the team formation mechanism. In order to promote this understanding, three models were developed in three different environments, which were the *software development industry*, *game play* and *collaborative learning*.

In all of these three models, the contribution of this model was not on the particular simulation results, but in demonstrating the ability of the modelling and simulation approaches to generate interesting emergent effects based on personality as measured by MBTI parameterizations.

12.1.6 Chapter 7

In Chapter 7, a team formation model was developed to predict and explain self-assembly behaviour in temporary teams. This model was re-used and empirically tested in Chapter 9 and Chapter 10. In Chapter 7, six factors were hypothesized to be involved in the formation of the self-assembly teams:

- The effect of ***familiarity*** on the teammate selection: We assume being familiar with other teammates improve the likelihood of being chosen for the future teams.
- The effect of ***past performance*** on the teammate selection: We assume being successful or unsuccessful plays an important role in the future team selection.
- The effect of ***Feeling personality*** (T-F) on the familiarity: Familiarity is assumed to be related to Feeling-Thinking personality dimension and for those with a Feeling

personality, familiarity with the other teammates is more important as compared to those with a Thinking personality.

- The effect of ***Sensing personality*** (N-S) on the past performance: Past performance is assumed to be related to the Sensing personality and those with Sensing personality put more weight on past performance when they choose a teammate.
- The effect of ***Extraverted personality*** (E-I) on the connections: Having more connection means being more familiar with them. Since Extraverts socialize with people and make connections, it is assumed that Extraverts will have more connections.
- The effect of ***Perceiving personality*** (J-P) on an individual changing the team: It is assumed that having a perceiving personality increases the likelihood of an individual's desire to join a new team.

Upon developing this model, experiments were conducted to investigate the relationship between agents' personalities and their performance. It was observed that the agents' scores were positively correlated with Extraversion, Thinking, and Perceiving personalities.

Moreover, in order to analyze the team evolution, the most repeated team compositions for two types of tasks were studied: structured and open-ended. The simulations yielded some interesting results. For example, for structured tasks the individuals mostly preferred to form teams with low extraverted personality. In contrast, for open-ended tasks highly Extraverted personality was often preferred. A simple explanation for that is open-ended tasks require more communication and Extraverted team members can facilitate this communication.

12.1.7 Chapter 8

In Chapter 8, in order to demonstrate the usability of the team formation model that was developed in Chapter 7, real data from the PEP development teams in Python was collected. Since the personalities of developers in the PEPs were not accessible, a model was developed to predict personality from the linguistic styles' of developers. In this chapter, by using a large dataset from Quora, the relationship between personality as measured by MBTI and a broad range of LIWC variables was extracted. These correlations were cross tested in two more social networking websites: College Confidential and Reddit. The results showed the validity of our model, and we employed this model with confidence to reveal the personality of PEPs developers for use in our agent-based model. Then texts written by the members of PEPs teams were gathered from their public activities on the internet such as their blogs and tweets, and we employed our computation method to compute the personality of the PEP developers.

12.1.8 Chapter 9

Chapter 9, by extracting knowledge from PEPs data, explored the hypothesis about the relationship between team performance and personality. It was assumed that software development tasks could be categorized as open ended tasks. By using a Bayesian model and the data extracted in Chapter 8 about the personalities of PEP developers, the hypothesis that software development tasks can be considered open-ended, and that heterogeneous teams improve the performance of such teams was tested. The results confirmed these hypotheses.

12.1.9 Chapter 10

In Chapter 10, the data and knowledge extracted in Chapter 8 were employed to assess the hypothesis for team formation in Chapter 7. By comparing the real team composition in PEPs and predicted team composition, the impact of the model and the contributions of various factors were discovered. In order to investigate the extent to which the hypotheses explained the behaviour of PEPs' developers, a cross-validation procedure was used and the contributions of our hypotheses in the prediction of team-assembly were examined. The simulation results showed that a combination of some social hypotheses helped improve the correct prediction of some team compositions in the PEPs (i.e. about 15%). This underlined the potential of agent-based simulations for predicting team composition. The results of different combinations of the hypotheses were compared to examine the reliability and influence of these hypotheses. This indicated that four main factors of the 6 factors presented in Chapter 7 positively impacted the accuracy of our model:

- The agents' personality regarding the probability of changing teams (Perceiving personality).
- The agents' personality regarding the other teammates (Feeling personality).
- The sense of familiarity between the agents.

- The awareness of past success in previous team formation.

Furthermore, in the main model up to this point, the influences of familiarity and previous performance were weighted equally. In order to evaluate the relative importance of these factors, more experiments were conducted, and adjusted weight was assigned to the familiarity and previous performances. Moreover, new simulation-based experiments were conducted to set thresholds for familiarity and past performance. The best performing model took a threshold value 1 for the past performance and 2 for familiarity. By evaluating various values of the parameters to our model, we could improve the accuracy of our model by up to 14.9%.

12.1.10 Chapter 11

In Chapter 11, some interesting rules and insights extracted about the relationship between personality and team performance were provided. The previous chapters had simplified the problem of the relationship between team personality of a team and their performance. Using these detailed rules could improve the modelling of team formation behavior. However, we note that there is no global formula for the relationship between personality and team composition, and what we have demonstrated is from the participants of the PEPs project. Various factors such as the structure of tasks and the nature of organizations should be taken into consideration in future experiments.

Chapter 11 provides a methodological approach for studying and managing the relationship between team personalities and performance. To do that, the data set and the computational model to determine the relationship between personality as measured by MBTI and the LIWC dimensions, which were explained in Chapter 8, was employed. An association-rule mining algorithm was employed to extract knowledge about the relationships between teams' performances and their personalities as measured by MBTI profiles.

The extracted rules suggested that heterogeneity improves the teams' efficiency, especially heterogeneity in terms of the iNtuition-Sensing dimension and the Judging-Perceiving dimension. Moreover, we discovered that some personality types improve the efficiency of teams in PEPs, including the Introverted, Judging, Feeling and iNtuition personalities.

12.2 Research Contribution

The primary objective of this research has been to investigate the role of personality in team behaviour, with an emphasis on developing a model that would enable the study of self-assembly teams in software projects. By simulating team formation using an agent-based model, the influence and contribution of different factors have been found and analysed. The contributions of this thesis can be divided into methodological and practical contributions as presented in Table 12.1. Our agent-based models can be used for conducting various "what-if" analyses by simulating the behaviour of teams under different circumstances. These simulations can demonstrate the role of team formation in team performance and reveal the main factors that affect the formation and performance of teams. In addition to these methodological contributions, this thesis has some practical contributions which are associated with new techniques for discovering and assessing the factors that affect team formation, team performance, and writing styles. The main contributions of this thesis are embodied in the following five aspects:

1. We developed an agent-based modelling approach that can show the collective team performance effects of individual team-members' personality attributes.

In order to show the effects of individual team members' attributes on team performance, we believe the mechanism behind team formation should be considered and understood. The three models developed in Chapters 3, 4 and 5 demonstrated that in addition to the skills and personalities within a team's composition, the team formation mechanism can influence the team's performance in complex environments. An agent-based modelling approach in conjunction with MBTI was applied in developing models to demonstrate team performance. These models indicated that a team model without covering self-assembly is not comprehensive.

2. We developed a useful instrument that can identify the relationship between the MBTI specification of personality from linguistic style.

In order to demonstrate the usability of the proposed model, it was necessary to extract information about the personalities of the PEPs' developers. Therefore, we developed a model that reveals the MBTI specification of the personalities of people by analysing their linguistic style. This model addressed the limitations of previous work in this area and was presented in Chapter 8.

3. We identified important factors that influence self-assembly behaviour.

We found that a combination of some social hypotheses helped us to correctly predict some teams in PEPs. This highlights the potential of simulation for understanding team formation. We compared the results of different combinations of our hypotheses to examine the reliability of our hypothesis. The results are presented in Chapter 10.

4. We demonstrated relationships between various combinations of personality types and overall team performance.

Throughout the thesis, we have examined the relationships between personality and team performance. Although, there is no unique formula that predicts the team efficiency in all contexts from the personality of team composition, this relationship can be customized based on many contextual factors, such as an organizational structure, tasks' types and so on, and the results can vary in different domains. In this connection, we made a hypothesis that heterogeneous composition would improve the efficiency of *software project teams*. This hypothesis is validated in Chapter 9. Nevertheless, since there is no global rule about the relationship between personality and team performance, we have developed a data-driven framework for building rules that determine the relationship between team personality and performance.

5. We developed a framework that can be used for Decision Support Systems (DSS) for team modelling.

We developed a framework that can be used for building tools that predict team compositions over a longer term. Managers can apply these tools for conducting various "what-if" analyses by simulating the behavior of teams under different circumstances.

Table 12.1 Practical and methodological contributions

Contribution	Practical Contribution	Methodological Contribution
1. Developing an agent-based modelling approach that can show the collective team performance effects of individual team-members' personality attributes		■
2. Developing an instrument that can be used to derive MBTI personality specification of individual from his/ her linguistic style	■	■
3. Identifying important factors that influence self-assembly behavior	■	
4. Demonstrating relationships between various combinations of personality types and overall team performance	■	■
5. Developing a framework that can be used for the development of a DSS that can be used in team-formation modelling	■	

12.3 Research Limitations

Our approach does have some recognized limitations:

- In Chapter 3, a computational model was introduced based on some rules extracted from the literature. It should be noted that the essence of this chapter is not to present the results but to show how a *team formation model* can play a role in team performance. The proposed computational model can be improved and validated by using a Delphi method and by having consultations with experts in the software development domain.
- Social roles, gender, age and other demographic factors which are not covered in this study might be involved in affecting the *team composition* and *team performance*.

- Our proposed rules about the linkages between personality and team performance in the software development industry as shown in Chapter 11 may not be applicable to other development contexts such as research-based teams, collaborative learning teams and so on.
- We made a handful of assumptions for building our team formation model. In this connection, some other personality-related factors have been neglected in this research, such as cohesion and groupthink, which might affect the behaviour of team members in the formation of teams. Also, the potential role of some other social factors such as membership, motivation, and authority could be investigated further.
- In order to develop a computational method that infers personality from linguistic styles, we calculated the correlations between Personality as separately measured by the MBTI and LIWC dimensions. To improve the accuracy of this approach, some machine learning algorithms such as Logistic Regression Model, SVM and Random Forest could be used to predict the personalities from the linguistic styles.
- In some cases, such as the computational method for inferring the personalities, we measured the correlations between variables significance levels of $p = 0.05$. In order to further validate the results some statistical techniques should be investigated to ensure that Type I errors have been controlled.
- Our dataset has some recognized limitations. The LIWC tool has a bias against individuals whose first language is not English, and we did not separate non-English users and developers from our dataset. Also, we had a limited number of developers' teams in a particular domain: in our case software development teams. Further experiments and validations must be performed before our correlations and results can be generalized to other domains.

12.4 Future Work

Future research should concentrate on the application of an agent-based team behaviour model. For example, the team formation model can be developed and used as a tool for managers to analyse the effect of various regulations in the organization. We suggested developing a framework and a Decision Support System (DSS) for team modelling in Chapter 6. This multi-agent framework can be used for researchers and managers to investigate effects on their employees' performances and effects on task allocation strategies in a real-world environment. This framework would not only cover the performance of a particular composition in terms of personality, but also cover team formation evolution.

Based on this framework, we can build a DSS that consists of two main parts: the first part is about extracting the rules and relationships between the personality of a team and its performance. In Chapter 8, we extracted some rules that determine the effect of personality on the team performance. However, we do not believe these rules can be generalized and likely there is no global formula for all organizations. The suggested rules might not be applicable for different organizations with different environments because of their different culture, organizational structure and task structure. They can take similar steps to the ones indicated in Chapter 11 to extract their own rules to find out the relationship between team performance and the personality of team.

Managers and designers, by selecting appropriate motivations and strategies (some discussed in Chapter 3, e.g. What are the best possible team configurations for avoiding future conflicts? or how does recruiting or firing someone with a specific personality affect team behaviour in the long term?), can influence the team formation in self-assembly teams. This DSS can be applied to crowd-sourcing websites, computer-supported co-operative work (CSCW), groupware, Computer-Supported Collaborative Learning (CSCL), and physical organizations. The tools built from this model can be used to simulate self-assembly environments and help managers, designers, teachers and others to find answers to some vexed questions such as: what is the implication for team performance if two people with specific personalities are working together on a particular task?

Furthermore, although the variances among the results in some of the models are mainly related to the randomness of values that are assigned to the agents' attributes, further investigation in the future is required to explain these variances.

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APPENDIXES

Appendix A

Fuzzy Rules

The following rules indicate the relationship between personality of agents and performance in the serious game agent based model.

- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is high AND O4 is high AND O5 is high THEN Performance is very high
- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is high AND O4 is high AND O5 is low THEN Performance is very high
- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is high AND O4 is low AND O5 is high THEN Performance is very high
- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is low AND O4 is high AND O5 is high THEN Performance is very high
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is high AND O4 is high AND O5 is high THEN Performance is very high
- IF the task is Open-ended AND O1 is low AND O2 is high AND O3 is high AND O4 is high AND O5 is high THEN Performance is very high
- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is high AND O4 is high AND O5 is high THEN Performance is high
- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is high AND O4 is high AND O5 is high THEN Performance is high
- IF the task is Open-ended AND O1 is low AND O2 is high AND O3 is low AND O4 is high AND O5 is high THEN Performance is high

- IF the task is Open-ended AND O1 is low AND O2 is high AND O3 is high AND O4 is low AND O5 is high THEN Performance is high
- IF the task is Open-ended AND O1 is low AND O2 is high AND O3 is high AND O4 is high AND O5 is low THEN Performance is high
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is low AND O4 is high AND O5 is high THEN Performance is high
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is high AND O4 is low AND O5 is high THEN Performance is high
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is high AND O4 is low AND O5 is high THEN Performance is high
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is high AND O4 is high AND O5 is low THEN Performance is high
- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is low AND O4 is low AND O5 is high THEN Performance is high
- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is low AND O4 is high AND O5 is low THEN Performance is high
- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is high AND O4 is low AND O5 is low THEN Performance is high
- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is high AND O4 is low AND O5 is low THEN Performance is high
- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is low AND O4 is high AND O5 is high THEN Performance is medium
- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is high AND O4 is low AND O5 is high THEN Performance is medium

- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is high AND O4 is high AND O5 is low THEN Performance is medium
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is low AND O4 is low AND O5 is high THEN Performance is medium
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is low AND O4 is high AND O5 is low THEN Performance is medium
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is high AND O4 is low AND O5 is low THEN Performance is medium
- IF the task is Open-ended AND O1 is high AND O2 is high AND O3 is low AND O4 is low AND O5 is low THEN Performance is medium
- IF the task is Open-ended AND O1 is high AND O2 is low AND O3 is low AND O4 is low AND O5 is low THEN Performance is low
- IF the task is Open-ended AND O1 is low AND O2 is high AND O3 is low AND O4 is low AND O5 is low THEN Performance is low
- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is high AND O4 is low AND O5 is low THEN Performance is low
- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is low AND O4 is high AND O5 is low THEN Performance is low
- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is low AND O4 is low AND O5 is high THEN Performance is low
- IF the task is Open-ended AND O1 is low AND O2 is low AND O3 is low AND O4 is low AND O5 is low THEN Performance is low
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is high AND S4 is high AND S5 is high AND S6 is high THEN Performance is high

- IF the task is Structured AND S1 is low AND S2 is high AND S3 is high AND S4 is high AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is low AND S3 is high AND S4 is high AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is low AND S4 is high AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is high AND S4 is low AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is high AND S4 is high AND S5 is low AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is high AND S4 is high AND S5 is high AND S6 is low THEN Performance is high
- IF the task is Structured AND S1 is low AND S2 is low AND S3 is high AND S4 is high AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is low AND S4 is high AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is high AND S4 is low AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is high AND S4 is low AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is high AND S4 is high AND S5 is low AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is high AND S4 is high AND S5 is high AND S6 is low THEN Performance is high

- IF the task is Structured AND S1 is high AND S2 is low AND S3 is low AND S4 is high AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is low AND S3 is low AND S4 is high AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is low AND S3 is high AND S4 is low AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is low AND S3 is high AND S4 is high AND S5 is low AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is low AND S3 is high AND S4 is high AND S5 is high AND S6 is low THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is low AND S4 is low AND S5 is high AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is low AND S4 is high AND S5 is low AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is low AND S4 is high AND S5 is high AND S6 is low THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is high AND S4 is low AND S5 is low AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is high AND S4 is low AND S5 is low AND S6 is high THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is high AND S4 is low AND S5 is high AND S6 is low THEN Performance is high
- IF the task is Structured AND S1 is high AND S2 is high AND S3 is high AND S4 is high AND S5 is low AND S6 is low THEN Performance is high

- IF the task is Structured AND S1 is low AND S2 is low AND S3 is low AND S4 is high AND S5 is high AND S6 is high THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is low AND S3 is high AND S4 is low AND S5 is high AND S6 is high THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is low AND S3 is high AND S4 is high AND S5 is low AND S6 is high THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is low AND S3 is high AND S4 is high AND S5 is high AND S6 is low THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is low AND S3 is high AND S4 is low AND S5 is high AND S6 is high THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is low AND S3 is high AND S4 is high AND S5 is low AND S6 is high THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is low AND S3 is high AND S4 is high AND S5 is high AND S6 is low THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is low AND S4 is low AND S5 is high AND S6 is high THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is low AND S4 is high AND S5 is low AND S6 is high THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is low AND S4 is high AND S5 is high AND S6 is low THEN Performance is medium
- IF the task is Structured AND S1 is low AND S2 is high AND S3 is high AND S4 is high AND S5 is high AND S6 is low THEN Performance is medium

- IF the task is Structured AND S1 is low AND S2 is low AND S3 is low AND S4 is low AND S5 is low AND S6 is low THEN Performance is low.

APPENDIX B

The Correlations Between Personality as measured by MBTI and LIWC Dimension

The following table indicates the correlations between Personality as measured by MBTI and LIWC Dimension

LIWC	Judging	Thinking	iNtution	Extraverted	Introverted	Sensing	Feeling	Perceiving
WPS	0.012	0.042	-0.098	.131*	-0.12	0.098	-0.056	-0.012
Sixltr	-0.027	.197**	-0.017	.165*	-.167*	0.017	-.191**	0.027
Dic	0.083	-.138*	0.015	-.153*	.153*	-0.015	0.121	-0.083
Unique	-0.051	-.148*	-0.099	.233**	-.238**	0.099	.165*	0.051
Pronoun	0.041	-0.122	-0.025	-0.105	0.102	0.025	0.115	-0.041
I	0.066	-.161*	-0.05	-0.006	0.002	0.05	.147*	-0.066
We	-0.031	-0.009	.158*	0.037	-0.031	-.158*	0.006	0.031
Self	0.055	-.159*	-0.001	0.004	-0.007	0.001	.144*	-0.055
You	0.002	-0.029	-0.075	-.131*	.134*	0.075	0.045	-0.002
Other	0.013	-0.023	0.016	-0.016	0.009	-0.016	0.003	-0.013
Negate	0.082	0.021	0.055	-.243**	.241**	-0.055	-0.029	-0.082
Assent	.134*	-0.115	-0.053	-0.108	0.109	0.053	0.127	-.134*
Article	-0.055	0.02	-0.011	0.038	-0.042	0.011	-0.018	0.055
Preps	0.035	0.109	0.015	0.082	-0.069	-0.015	-0.106	-0.035
Number	0.105	0.019	0.061	-.149*	.147*	-0.061	-0.022	-0.105
Affect	0.096	-.173**	-0.005	-0.115	0.109	0.005	.150*	-0.096
Posemo	0.034	-.200**	-0.038	0.026	-0.021	0.038	.185**	-0.034
Posfeel	0.025	-.258**	-0.064	-0.041	0.045	0.064	.244**	-0.025
Optim	0.076	-0.018	-.139*	0.085	-0.081	.139*	0.014	-0.076
Negemo	0.121	-0.061	0.037	-.218**	.204**	-0.037	0.04	-0.121
Anx	0.076	-0.049	0.07	-.156*	.147*	-0.07	0.037	-0.076
Anger	0.118	0.008	0.014	-.133*	0.123	-0.014	-0.024	-0.118
Sad	0.061	-0.112	-0.042	-.186**	.177**	0.042	0.111	-0.061
Cogmech	0.036	-0.02	0.087	-.193**	.194**	-0.087	0.019	-0.036
Cause	0.091	0.044	.182**	-.183**	.189**	-.182**	-0.046	-0.091
Insight	0.023	-0.028	0.101	-.140*	.138*	-0.101	0.018	-0.023

Discrep	0.017	-0.019	-0.014	-.155*	.161*	0.014	0.029	-0.017
Inhib	-0.02	0.07	-0.09	0.002	-0.013	0.09	-0.076	0.02
Tentat	0.081	-0.018	0.079	-.200**	.200**	-0.079	0.026	-0.081
Certain	0.019	-.180**	-0.025	0.085	-0.085	0.025	.166*	-0.019
Senses	0.004	-0.117	0.057	-0.118	0.108	-0.057	0.114	-0.004
See	-0.083	0.006	0.041	0.058	-0.066	-0.041	0.017	0.083
Hear	0.091	-0.053	0.043	-.158*	.152*	-0.043	0.036	-0.091
Feel	0.008	-.148*	0.053	-0.116	0.113	-0.053	.136*	-0.008
Social	0.104	-0.049	-0.008	-.133*	.132*	0.008	0.04	-0.104
Comm	.180**	0.04	-0.015	-.143*	.135*	0.015	-0.046	-.180**
Othref	0.005	-0.047	-0.015	-0.095	0.096	0.015	0.047	-0.005
Friends	0.094	-0.113	0.028	-0.056	0.055	-0.028	0.1	-0.094
Family	.145*	-0.116	0.002	-0.057	0.055	-0.002	0.1	-.145*
Humans	.150*	-0.059	0.033	-.136*	.133*	-0.033	0.039	-.150*
Time	0.015	-.207**	-0.127	0.001	0.009	0.127	.201**	-0.015
Past	0.005	-0.049	0.027	-0.025	0.02	-0.027	0.042	-0.005
Present	-0.002	-0.034	0.063	-.177**	.178**	-0.063	0.028	0.002
Future	0.035	-0.036	0.03	-0.105	0.105	-0.03	0.045	-0.035
Space	-0.052	-0.022	-0.057	0.078	-0.066	0.057	0.036	0.052
Up	0	-0.053	-0.109	0.099	-0.086	0.109	0.065	0
Down	-0.046	0.085	-0.03	0.036	-0.038	0.03	-0.073	0.046
Incl	-0.076	-0.041	0.046	.171**	-.166*	-0.046	0.033	0.076
Excl	0.001	0.03	0.059	-.147*	.151*	-0.059	-0.047	-0.001
Motion	-0.059	-0.101	-0.032	0.097	-0.098	0.032	0.117	0.059
Occup	-0.023	.141*	-.145*	.212**	-.200**	.145*	-0.127	0.023
School	-0.003	0.023	-0.105	.151*	-.151*	0.105	-0.006	0.003
Job	-0.059	.182**	-0.108	.248**	-.219**	0.108	-.175**	0.059
Achieve	0.017	0.109	-0.105	0.027	-0.019	0.105	-0.111	-0.017
Leisure	-0.022	-0.047	-0.071	0.12	-0.118	0.071	0.034	0.022
Home	-0.002	-0.095	0.008	0.029	-0.022	-0.008	0.088	0.002
Sports	0.015	0.084	-.141*	0.062	-0.058	.141*	-0.09	-0.015
TV	0.036	-0.081	-0.04	-0.014	0.008	0.04	0.074	-0.036
Music	-0.088	-0.065	0.032	.163*	-.168*	-0.032	0.057	0.088
Money	0.023	.183**	-0.092	0.084	-0.059	0.092	-.181**	-0.023
Metaph	-0.024	-0.026	0.013	0.105	-0.11	-0.013	0.014	0.024
Relig	-0.017	-0.012	0.023	0.105	-0.109	-0.023	0.003	0.017
Death	-0.034	-0.049	-0.027	0.043	-0.051	0.027	0.035	0.034
Physcal	-0.032	-.254**	0.003	-0.116	0.108	-0.003	.244**	0.032
Body	0.004	-.196**	-0.009	-.155*	.146*	0.009	.192**	-0.004
Sexual	-0.073	-.234**	0.083	-0.015	0.018	-0.083	.215**	0.073

Eating	-0.023	-0.059	-0.052	-0.038	0.032	0.052	0.058	0.023
Sleep	-0.098	-.246**	-0.042	-0.013	0.01	0.042	.241**	0.098
Groom	0.013	-0.094	0.084	-.170**	.163*	-0.084	0.078	-0.013
Swear	-0.018	-0.01	-0.014	0.097	-0.104	0.014	0.004	0.018
Nonfl	0.046	-0.041	-0.05	-0.027	0.023	0.05	0.034	-0.046
Fillers	-0.004	-0.001	0.018	-0.082	0.082	-0.018	0.005	0.004
Period	-0.018	-0.109	-0.085	-0.011	0.006	0.085	0.112	0.018
Comma	-0.072	0.017	0.08	0.007	-0.003	-0.08	-0.002	0.072
Colon	0.097	-0.012	-.173**	0.009	-0.014	.173**	0.012	-0.097
SemiC	-0.004	0.006	0.001	-0.015	0.007	-0.001	-0.01	0.004
QMark	0.092	0.031	-0.113	-0.08	0.076	0.113	-0.031	-0.092
Exclam	-0.064	-.186**	-0.055	0.015	-0.018	0.055	.181**	0.064
Dash	-0.112	0.011	0.039	0.109	-0.105	-0.039	-0.002	0.112
Quote	0.013	0.115	-0.055	-0.016	0.017	0.055	-0.125	-0.013
Apostro	0.044	0.063	0.025	-0.062	0.061	-0.025	-0.075	-0.044
Parenth	-0.029	0.052	0.044	0.104	-0.099	-0.044	-0.059	0.029
OtherP	0.008	.130*	-0.119	0.012	-0.002	0.119	-.132*	-0.008
AllPct	-0.015	0.024	-0.091	0.019	-0.017	0.091	-0.021	0.015

APPENDIX C

PEPs Team

id	Final status	date	Contributor
1	Active	13/07/2000	Warsaw, Hylton, Goodger, Coghlan
207	Final	15/07/2000	GvR, Ascher
208	Final	15/07/2000	Schemenauer, Lemburg
209	Withdrawn	15/07/2000	Barrett, Oliphant
218	Final	31/07/2000	Wilson, Hettinger
228	Withdrawn	5/11/2000	Zadka, GvR
102	Superseded	10/01/2001	Baxter, Warsaw, GvR
234	Final	4/02/2001	Yee, GvR
6	Active	15/03/2001	Aahz, Baxter
237	Final	16/03/2001	Zadka, GvR
238	Final	16/03/2001	Zadka, GvR
239	Rejected	16/03/2001	Craig, Zadka
240	Rejected	16/03/2001	Craig, Zadka
246	Rejected	16/03/2001	Martelli, Evans
251	Final	18/04/2001	Warsaw, GvR
255	Final	5/06/2001	Schemenauer, Peters, Hetland
257	Active	6/06/2001	Goodger, GvR
8	Active	6/07/2001	GvR, Warsaw, Coghlan
263	Final	18/07/2001	Lemburg, von Löwis
101	Active	22/08/2001	Warsaw, GvR

225	Deferred	19/09/2001	Zhu, Lielens
282	Final	15/02/2002	Sajip, Mick
284	Rejected	6/03/2002	Eppstein, Ewing
12	Active	27/08/2002	Goodger, Warsaw
302	Final	20/12/2002	JvR, Moore
306	Withdrawn	29/01/2003	Hudson, Diederich, Coghlan, Peterson
307	Final	29/01/2003	GvR, Peters
308	Final	7/02/2003	GvR, Hettinger
310	Rejected	10/02/2003	Hudson, Moore
312	Deferred	14/02/2003	Suzi, Martelli
314	Final	12/04/2003	Kuchling, Jones
315	Rejected	2/05/2003	Hettinger, Carroll
320	Final	29/07/2003	Warsaw, Hettinger, Baxter
320	Final	29/07/2003	Warsaw, Hettinger, Baxter
326	Rejected	4/01/2004	Carlson, Reedy
326	Rejected	4/01/2004	Carlson, Reedy
342	Final	11/05/2005	GvR, Eby
343	Final	14/05/2005	GvR, Coghlan
352	Final	28/10/2005	Cannon, GvR
356	Final	8/02/2006	Norwitz, GvR, Baxter
358	Final	22/02/2006	Schemenauer, GvR
361	Final	30/06/2006	Norwitz, Warsaw
3107	Final	22/12/2006	Winter, Lownds
3118	Final	9/04/2007	Oliphant, Banks

3119	Final	18/04/2007	GvR, Talin
3126	Rejected	30/04/2007	Jewett, Hettinger
367	Superseded	1/05/2007	Spealman, Delaney
3116	Final	15/05/2007	Stutzbach, GvR, Verdone
3135	Final	7/06/2007	Spealman, Delaney, Ryan
371	Final	28/05/2008	Noller, Oudkerk
3140	Rejected	29/05/2008	Broytmann, Jewett
372	Final	16/06/2008	Ronacher, Hettinger
381	Draft	21/04/2009	Ziadé, v. Löwis
3145	Withdrawn	7/09/2009	Pruitt, McCreary, Carlson
385	Final	25/09/2009	Ochtman, Pitrou, Brandl
3003	Final	3/11/2009	Cannon, Noller, GvR
3146	Withdrawn	20/01/2010	Winter, Yasskin, Kleckner
444	Deferred	15/09/2010	McDonough, Ronacher
394	Active	4/05/2011	Staley, Coghlan
397	Final	22/05/2011	Hammond, v. Löwis
408	Rejected	27/01/2012	Coghlan, Bendersky
411	Accepted	10/02/2012	Coghlan, Bendersky
414	Final	25/02/2012	Ronacher, Coghlan
418	Final	27/05/2012	Simpson, Jewett, Turnbull, Stinner
422	Deferred	5/06/2012	Coghlan, Urban
426	Draft	31/08/2012	Coghlan, Holth, Stufft
434	Active	19/02/2013	Rovito, Reedy
438	Accepted	15/05/2013	Krekel, Meyer

440	Accepted	30/05/2013	Coghlan, Stufft
452	Final	17/08/2013	Kuchling, Heimes
453	Final	20/09/2013	Stufft, Coghlan
472	Draft	13/07/2014	Borini, Martinot-Lagarde
475	Draft	24/07/2014	Natali, Stinner
477	Final	31/08/2014	Stufft, Coghlan
479	Accepted	15/11/2014	Angelico, GvR

APPENDIX D

Personality of PEP's Developers Based on Their Text Usage

Developers' names	Introverted	Sensing	Feeling	Perceiving
Angelico	23.05	56.09	46.02	76.90
Ascher	98.62	12.60	16.31	15.41
Banks	73.42	21.52	62.21	37.53
Barrett	22.07	85.38	20.32	73.83
Baxter	69.66	34.10	80.62	48.47
Bendersky	51.00	33.60	61.14	77.53
Borini	13.58	73.04	43.66	79.29
Brandl	36.02	86.05	86.60	86.82
Broytmann	35.29	37.17	100.00	79.89
Cannon	70.96	15.36	61.39	46.68
Carlson	69.33	15.24	43.96	80.81
Carroll	32.98	55.33	34.07	83.81
Coghlan	71.31	4.30	85.98	76.02
Craig	44.73	49.37	39.08	2.85
Delaney	53.08	69.38	24.21	73.51
Diederich	29.61	43.61	0.00	65.83
Eby	100.00	2.25	78.93	5.30
Eppstein	20.47	68.45	44.40	73.27
Evans	15.37	83.60	29.52	67.41

Ewing	24.49	80.46	38.80	58.77
Goodger	8.58	43.72	53.70	12.10
GvR	86.88	43.61	67.50	56.02
Hammond	91.30	67.09	87.07	3.31
Heimes	98.05	0.00	98.55	2.27
Hetland	57.80	48.30	12.09	73.93
Hettinger	41.26	46.61	39.01	71.61
Holth	50.50	37.63	72.07	71.69
Hudson	12.49	88.05	35.83	51.40
Hylton	8.79	42.07	53.10	81.20
Jewett	39.48	37.73	69.79	71.23
Jones	51.28	37.04	71.68	78.77
Kleckner	53.01	26.25	58.93	81.40
Krekel	52.00	49.60	28.42	58.62
Kuchling	24.13	90.28	22.12	100.00
Lemburg	41.02	54.78	77.41	33.13
Lielens	18.74	88.07	36.07	60.99
Lownds	26.69	4.72	82.63	7.09
Martelli	21.51	87.77	23.04	83.69
Martinot-Lagarde	18.02	88.09	36.03	60.02
McCreary	90.02	88.30	18.03	18.52
McDonough	60.36	33.98	63.95	55.95
Meyer	51.01	33.60	61.16	77.53

Mick	17.67	78.60	44.78	72.43
Moore	52.56	72.31	45.57	43.85
Natali	49.09	98.03	21.03	87.50
Noller	76.40	25.85	53.25	34.50
Norwitz	33.70	44.32	51.29	92.89
Ochtman	62.69	57.56	43.02	33.65
Oliphant	29.76	79.08	36.85	66.70
Oudkerk	54.54	44.98	45.08	58.56
Peters	61.71	22.80	49.78	3.88
Peterson	71.31	4.30	85.98	76.02
Pitrou	66.98	2.05	69.28	39.21
Pruitt	45.65	32.47	18.02	57.05
Reedy	38.93	61.85	64.27	90.78
Ronacher	73.48	24.75	37.66	75.77
Rovito	29.88	98.21	54.07	72.07
Ryan	90.46	3.68	87.35	7.36
Sajip	68.58	36.83	84.77	10.31
Schemenauer	76.85	6.56	41.71	15.11
Simpson	45.50	19.47	92.11	72.98
Spealman	31.09	74.67	43.17	34.80
Staley	50.23	6.22	78.89	77.90
Stinner	50.14	34.29	60.60	93.40
Stufft	55.04	21.62	44.73	76.69

Stutzbach	81.36	12.48	89.95	22.04
Suzi	12.49	44.05	35.83	51.40
Talin	73.41	11.91	92.04	22.04
Turnbull	56.90	34.28	62.73	77.56
Urban	29.63	100.00	58.97	94.24
Verdone	75.36	25.94	92.29	39.56
von Löwis	73.81	11.00	21.56	69.83
Warsaw	39.34	19.91	53.64	81.46
Wilson	52.67	3.43	72.95	23.78
Winter	43.39	29.77	52.54	59.83
Yasskin	37.22	77.15	0.00	96.62
Yee	66.53	2.18	58.92	5.19
Zadka	68.82	29.06	82.99	8.21
Zhu	13.06	73.51	43.58	79.98
Ziadé	64.54	38.82	74.76	65.01

APPENDIX E

PEP Teams Personality

Id	TPE_I	TPE_S	TPE_F	TPE_P	TPD_I	TPD_S	TPD_F	TPD_P
1	32.01	27.50	61.61	62.69	671.62	267.81	198.15	858.02
207	92.75	28.10	41.91	35.72	34.43	240.33	655.13	412.13
208	58.93	30.67	59.56	24.12	321.01	581.19	318.67	81.17
209	25.92	82.23	28.59	70.27	14.79	9.93	68.35	12.71
218	46.96	43.02	55.98	47.70	32.52	12.88	287.89	572.09
228	77.85	36.33	75.25	32.11	81.57	52.89	59.99	571.38
102	65.30	32.54	67.26	61.98	386.20	94.77	121.38	199.19
234	76.71	36.39	63.21	50.60	103.62	52.02	18.42	29.31
6	59.00	40.11	57.41	57.85	113.63	36.16	10.35	88.01
237	77.85	36.33	75.25	32.11	81.57	52.89	59.99	571.38
238	77.85	36.33	75.25	32.11	81.57	52.89	59.99	571.38
239	56.78	39.22	61.04	5.53	145.06	103.13	482.00	7.18
240	56.78	39.22	61.04	5.53	145.06	103.13	482.00	7.18
246	18.44	85.69	26.28	75.55	9.44	4.35	10.49	66.25
251	63.11	31.76	60.57	68.74	565.03	140.33	48.04	161.83
255	65.45	25.89	34.53	42.64	67.49	295.03	262.43	583.75
257	47.73	43.66	60.60	34.06	1532.90	0.00	47.64	482.20
8	65.85	22.61	69.04	71.17	391.61	261.16	175.52	119.67
263	57.41	32.89	49.48	51.48	268.78	479.05	779.77	336.79
101	63.11	31.76	60.57	68.74	565.03	140.33	48.04	161.83
225	15.90	80.79	39.82	70.48	8.09	52.98	14.12	90.12
282	43.12	57.72	64.78	41.37	648.02	436.32	399.80	964.87
284	22.48	74.46	41.60	66.02	4.05	36.08	7.84	52.59
12	23.96	31.82	53.67	46.78	236.61	141.71	0.00	1202.71
302	65.69	42.48	59.31	26.43	172.17	889.41	188.54	303.35
306	53.35	24.35	46.19	70.70	1182.90	379.69	1026.20	194.93
307	74.30	33.21	58.64	47.45	158.47	108.17	78.56	73.38
308	64.07	45.11	53.26	63.82	520.38	2.25	202.92	60.82
310	32.53	58.18	40.70	47.62	401.40	199.64	23.72	14.28
312	32.61	83.41	28.96	80.50	123.16	18.99	35.08	10.18
314	37.70	63.66	46.90	89.38	184.25	708.44	614.19	112.71
315	37.12	50.97	36.54	77.71	17.15	19.03	6.11	37.16
320	50.09	33.54	57.76	67.18	192.12	118.90	297.06	191.23

320	50.09	33.54	57.76	67.18	192.12	118.90	297.06	191.23
326	54.13	38.54	54.12	85.80	231.02	543.15	103.12	24.86
326	54.13	38.54	54.12	85.80	231.02	543.15	103.12	24.86
342	93.44	35.43	73.22	65.66	43.00	66.88	32.62	92.94
343	79.10	23.95	76.74	66.02	60.65	386.30	85.38	100.05
352	78.92	29.48	64.45	51.35	63.38	199.45	9.33	21.80
356	63.41	40.67	66.47	65.79	491.02	21.73	143.99	376.75
358	81.87	25.08	54.60	35.56	25.17	343.04	166.37	418.31
361	36.52	32.12	52.46	87.18	7.98	148.95	1.39	32.70
3107	35.04	36.25	67.59	67.46	69.78	41.93	226.29	58.18
3118	51.59	50.30	49.53	52.12	476.47	828.28	160.67	212.75
3119	80.15	27.76	79.77	39.03	45.41	251.23	150.58	288.53
3126	40.37	42.17	54.40	71.42	0.79	19.70	236.76	0.04
367	42.08	72.02	33.69	54.15	120.91	6.99	89.91	374.64
3116	71.20	27.34	79.92	45.87	108.47	162.46	252.07	505.52
3135	58.21	49.24	51.58	38.55	120.91	6.99	89.91	374.64
371	65.47	35.41	49.16	46.53	119.41	91.43	16.70	144.83
3140	37.39	37.45	84.89	75.56	4.39	0.08	228.21	18.76
372	57.37	35.68	38.34	73.69	259.46	119.42	0.46	4.33
381	69.17	24.91	48.16	67.42	21.47	193.48	707.66	5.82
3145	68.33	45.33	26.67	52.13	328.65	972.40	149.47	658.82
385	55.23	48.55	66.30	53.23	187.61	1216.50	321.05	569.54
3003	78.08	28.27	60.72	45.73	43.67	135.90	34.09	77.64
3146	44.54	44.39	37.16	79.28	42.22	538.51	697.13	227.77
444	66.92	29.37	50.81	65.86	42.98	21.31	172.83	98.25
394	60.77	5.26	82.44	76.96	111.04	0.93	12.56	0.89
397	66.16	50.94	82.24	23.22	632.19	14.77	23.33	98.24
408	61.15	18.95	73.56	76.77	103.11	214.62	154.26	0.57
411	61.15	18.95	73.56	76.77	103.11	214.62	154.26	0.57
414	72.39	14.52	61.82	75.90	1.17	104.59	583.74	0.02
418	48.00	31.44	71.31	78.79	40.64	49.73	155.82	76.47
422	50.47	52.15	72.47	85.13	434.26	2289.80	182.48	83.02
426	60.91	30.96	79.03	73.86	79.81	49.05	293.70	4.91
434	34.40	80.03	59.17	81.43	20.50	330.48	26.01	87.51
438	51.50	41.60	44.79	68.08	0.25	64.04	268.00	89.37
440	63.17	20.46	90.35	86.36	66.18	261.17	19.11	106.81
452	61.09	45.14	60.33	51.14	1366.10	2037.50	1460.50	2387.75
453	63.17	20.46	90.35	86.36	66.18	261.17	19.11	106.81
472	15.80	80.56	39.84	69.66	4.93	56.68	14.55	92.82

475	55.91	87.79	35.59	60.89	46.51	104.79	211.76	707.88
477	63.17	20.46	90.35	86.36	66.18	261.17	19.11	106.81
479	54.97	49.85	56.76	66.46	1018.70	38.96	115.34	109.08

APPENDIX F

PEPs Team Personality Label

ID	TPE_I	TPE_S	TPE_F	TPE_P	TPD_I	TPD_S	TPD_F	TPD_P	Status
1	LOW	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	Active
207	HIGH	LOW	HIGH	LOW	LOW	HIGH	HIGH	HIGH	Success
208	HIGH	LOW	HIGH	LOW	HIGH	HIGH	HIGH	LOW	Success
209	LOW	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	Fail
218	HIGH	HIGH	HIGH	LOW	LOW	LOW	HIGH	HIGH	Success
228	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	HIGH	Fail
102	HIGH	LOW	HIGH	HIGH	HIGH	LOW	LOW	HIGH	Fail
234	HIGH	LOW	HIGH	HIGH	HIGH	LOW	LOW	LOW	Success
6	HIGH	LOW	HIGH	HIGH	LOW	LOW	LOW	LOW	Active
237	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	HIGH	Success
238	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	HIGH	Success
239	HIGH	LOW	HIGH	LOW	LOW	LOW	HIGH	LOW	Fail
240	HIGH	LOW	HIGH	LOW	LOW	LOW	HIGH	LOW	Fail
246	LOW	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	Fail
251	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	LOW	HIGH	Success
255	HIGH	LOW	LOW	LOW	LOW	HIGH	HIGH	HIGH	Success
257	LOW	HIGH	HIGH	LOW	HIGH	LOW	LOW	HIGH	Active
8	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	LOW	Active
263	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	Success
101	HIGH	LOW	HIGH	HIGH	HIGH	LOW	LOW	HIGH	Active

225	LOW	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	Fail
282	HIGH	HIGH	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	Success
284	LOW	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	Fail
12	LOW	LOW	HIGH	HIGH	HIGH	LOW	LOW	HIGH	Active
302	HIGH	LOW	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	Success
306	HIGH	LOW	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	Fail
307	HIGH	LOW	HIGH	LOW	HIGH	HIGH	LOW	LOW	Success
308	HIGH	LOW	HIGH	HIGH	HIGH	LOW	HIGH	LOW	Success
310	LOW	HIGH	LOW	HIGH	HIGH	HIGH	LOW	LOW	Fail
312	LOW	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	Fail
314	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	Success
315	LOW	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	Fail
320	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	Success
320	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	Success
326	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	LOW	LOW	Fail
326	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	LOW	LOW	Fail
342	HIGH	LOW	HIGH	HIGH	LOW	LOW	LOW	LOW	Success
343	HIGH	LOW	HIGH	HIGH	LOW	HIGH	LOW	HIGH	Success
352	HIGH	LOW	HIGH	HIGH	LOW	HIGH	LOW	LOW	Success
356	HIGH	LOW	HIGH	HIGH	HIGH	LOW	HIGH	HIGH	Success
358	HIGH	LOW	HIGH	LOW	LOW	HIGH	HIGH	HIGH	Success
361	LOW	LOW	HIGH	HIGH	LOW	HIGH	LOW	LOW	Success
3107	LOW	LOW	HIGH	HIGH	LOW	LOW	HIGH	LOW	Success
3118	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	Success

3119	HIGH	LOW	HIGH	LOW	LOW	HIGH	HIGH	HIGH	Success
3126	LOW	LOW	HIGH	HIGH	LOW	LOW	HIGH	LOW	Fail
367	LOW	HIGH	LOW	HIGH	LOW	LOW	LOW	HIGH	Fail
3116	HIGH	LOW	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	Success
3135	HIGH	LOW	HIGH	LOW	HIGH	LOW	LOW	HIGH	Success
371	HIGH	LOW	HIGH	HIGH	HIGH	LOW	LOW	HIGH	Success
3140	LOW	LOW	HIGH	HIGH	LOW	LOW	HIGH	LOW	Fail
372	HIGH	LOW	LOW	HIGH	HIGH	HIGH	LOW	LOW	Success
381	HIGH	LOW	HIGH	HIGH	LOW	HIGH	HIGH	LOW	Active
3145	HIGH	HIGH	LOW	HIGH	HIGH	HIGH	LOW	HIGH	Fail
385	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	Success
3003	HIGH	LOW	HIGH	LOW	LOW	HIGH	LOW	HIGH	Success
3146	LOW	HIGH	LOW	HIGH	LOW	HIGH	HIGH	HIGH	Fail
444	HIGH	LOW	HIGH	HIGH	LOW	LOW	HIGH	LOW	Fail
394	HIGH	LOW	HIGH	HIGH	HIGH	LOW	LOW	LOW	Active
397	HIGH	HIGH	HIGH	LOW	HIGH	LOW	LOW	LOW	Success
408	HIGH	LOW	HIGH	HIGH	LOW	HIGH	HIGH	LOW	Fail
411	HIGH	LOW	HIGH	HIGH	LOW	HIGH	HIGH	LOW	Active
414	HIGH	LOW	HIGH	HIGH	LOW	HIGH	HIGH	LOW	Success
418	HIGH	LOW	HIGH	HIGH	LOW	LOW	HIGH	LOW	Success
422	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	LOW	Active
426	HIGH	LOW	HIGH	HIGH	LOW	LOW	HIGH	LOW	Active
434	LOW	HIGH	HIGH	HIGH	LOW	HIGH	LOW	LOW	Active
438	HIGH	HIGH	LOW	HIGH	LOW	LOW	HIGH	LOW	Active

440	HIGH	LOW	HIGH	HIGH	LOW	HIGH	LOW	HIGH	Active
452	HIGH	LOW	HIGH	HIGH	HIGH	HIGH	HIGH	HIGH	Success
453	HIGH	LOW	HIGH	HIGH	LOW	HIGH	LOW	HIGH	Success
472	LOW	HIGH	LOW	HIGH	LOW	LOW	LOW	LOW	Active
475	HIGH	HIGH	LOW	HIGH	LOW	HIGH	HIGH	HIGH	Success
477	HIGH	LOW	HIGH	HIGH	LOW	HIGH	LOW	HIGH	Success
479	HIGH	LOW	HIGH	HIGH	HIGH	LOW	HIGH	HIGH	Active