A Set of Rules for Constructing Gender-based Personality types' Composition for Software Programmer

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Abstract. The current era has been declared as technological era where both profit and no-profit organisations rely solely on software to cope with myriad issues they typically face. The growing demand for software has equally placed challenging tasks on workplaces to produce quality and reliable software. Unfortunately, software development industries have drastically failed to produce software in due time or even if software is produced in time but it fails to yield the desired results. Keeping this problem in view, this study tried to address this problem by offering team composition model lucrative for software development. For instance, Personality types, especially Introvert (I) and Extrovert (E) traits, of team members of software development are explored with gender diversity with a key focus on the programmer role. Moreover, descriptive and predictive approaches were applied to gain the hidden facts from data. The data of this study was taken from both academia and industry to establish the generalizability in the findings. Additionally, different personality traits composition was set based on gender which was not studied in previous studies. The findings of this research suggest that male-programmer should be composed of E trait of personality and, whereas female-programmer should be I. The overall findings contribute to serve the cause of software development team and also contribute to the existing literature on software development and its team composition.

Keywords: *Human aspects, Personality types, programmer, gender, software development, team composition, software engineering, rule-based, decision tree, rough sets.*

1. Introduction

In today's fast-paced technological era, software is a demand of various fields such as hospital and pharmacy, business, tutoring classes, road side restaurant to stared hotel, defense and even many more. In fact, these days software has earned its compulsory nature in different fields to attain their ultimate ends. Thus, the growing demand of software has ultimately set challenging task for software work place to supply the demand of reliable and quality software in time. As microeconomics explains that scanty supply of the demanded goods cause detrimental results [1], similarly, software development companies have badly failed to meet the demands of customers for software (or quality software) which is alarming and needs to be seriously addressed. The findings of the study by Standish group [2] asserted that there was only 6% of software developed against the demands of customers from the year 2003 until 2012. The study also confirmed that 52% of software was challenged whereas 42% software failed to meet the deadlines. Moreover, many studies in the past have also estimated that the ratio of IT development projects have continuously failed to achieve their desired ends [3]–[5].

Looking at the aspect of software projects' success, it is correlated to the human workforce aspects [6], [7]. In other words, the quality of software depends on the personality types of team members [8]–[11]. Gulla [5] also attributed ineffective team composition as one of seven key factors causing IT project failures. Hence, to form an effective software team composition, it is primarily important to take those team members who are adjustable and capable of working with well-formed team based on their personality types [12]. Though plethora of research has been carried out in the past to determine the ideal personality types for an effective teamwork in software engineering, yet this issue seems unresolved [13]–[15].

The current study, therefore, focuses on the advantages of diversity among team members in the workplace to gain the deep knowledge about demographic such as gender issues in team composition which acts as a precursor to inclusion. This view is also supported by Muchiri & Ayoko [16] where they proposed that cognitive task performance can also be affected by gender diversity and its solution helps in stimulating problem solving tasks. Hence, issue of demographic diversity i.e., culture and gender needs to be propagated in future research studies for making effective team composition for software development. [17].

2. RELATED WORK

The composition of ineffective teams is one of the prime reasons for less efficient performance and poor results in software project development [8]–[12][18]. Although many studies have been done in the past to suggest the suitable personality types and team composition for producing quality software in time, but the problem still seems persistent [19]–[21]. The problem stands unresolved because different researchers have proposed different types of models and theories suggesting different personality types and team composition for software development. As a result, they have not only caused ambiguity for software developers as whom to follow but also have failed to win the researchers' consensus for the lack of their reliability. For example, Gorla and Lam [18] suggested extrovert (E) personality type while Capretz and Ahmed [22] suggested introvert (I) personality type for programmers. Additionally, the model by Capretz and Ahmed [22] was based on job advertisements, hence a limited scope of findings. On the contrary, the model by Gorla and Lam [18] was based on empirical data collected merely from university students' users that cannot be generalized with industry practices. Hence, the most suitable personality types for team organization are still undefined since past research studies have established their findings and suggestions from irrelevant data. Cruz and da Silva [23] and MacDonell [24] have also confirmed that the models suggested in the past for team compositions were less effective and less efficient when they were implemented to obtain desired results. They also asserted that this prevailing situation has rather added ambiguity and uncertainty among practitioners.

Although number of research studies has been conducted in the field of social sciences to determine the relationship between gender and personality, but this aspect is still under researched in the field of software development. For instance, Richard & Busch [25] and Gilal et al., [26] claim that maturity in terms of personality and gender is a demand of software development research. This view has been supported by Trauth [27] who proposed that software development should have an improvement in the aspect of its theoretical work. In the same vein, Gilal et al., [26] carried out the study on type of personalities and gender for an effective team composition and strongly recommended the both aspects for an ideal team composition. Besides, the author also showed the concern for the variation of performance based on gender's personality types. For an example, female, working with a team dominated by male, will show less effective if the personality of female carries "E" trait. The findings of this study also determined that female-leader team will only be effective if the team consists of majority of female workers.

Myers-Brigs Type Indicator (MBTI) has been used 50 years ago as a source for identifying an individual's personality preferences and personality types which is not only useful for everyday life but also useful for making theories of Jung [37]. The pioneer of this MBTI was Katherine Cook Briggs and her daughter, Isabel Briggs Myers who successfully established interrelation between different theories of human behaviours such as theory of psychological types into practical use besides extensively studied work of Jung. The MBTI test allows individual personality type preferences to be classified in 16 types that results a combination of four dimensional pairs, which are Introversion (I) and Extroversion (E); Thinking (T) and Feeling (F); Sensing (S) and Intuitive (N) ; Judging (J) and Perceiving (P) [18][28]. Hence, these four dimensions have become the basis for the 16 possible personality combinations. Therefore, the current study used MBTI as a principal tool in assessing personality types amongst software team members because it has been widely used in the past research studies under the domain of software engineering due to its validity and reliability. [29]–[34].

3. METHODOLOGY

This study included team role, personality types, and gender as predictor variables (independent variable) whereas team performance was considered as an outcome variable dependent on the former predictor variables. Controlled experimented data was used to develop the rules for programmer role and the Myer Brigs Type Indicator (MBTI) instrument was used to measure the personality types of team members. Additionally, the programmer role was also examined and first pair of MBTI (i.e., Introvert and Extrovert) was seen comprehensively in this research.

The results of this study were extracted and validated by the research sample consisting of students from Universiti Utara Malaysia (UUM). The findings were further validated from industrial dataset collected from three different companies in order to gain general consents of practitioners. The dataset from university was divided into two elementary sets of training and testing that was divided to 70% and 30% standard ratios [35].

To develop the lucid picture of results, the experiments were divided into two stages. The first stage aimed at descriptive examination of factual figures of data necessary for understanding of the basic relations and behaviors of the data crucially important for giving a general consent. Whereas, the second stage was predictive experiments of data due for finding future trends from datasets. Furthermore, the basics of data (or descriptive stage) was explored and discussed by using descriptive analyses, frequency analyses, graphs and tables in SPSS and Microsoft Excel. For predictive model development in this study, decision tree and rough set approaches were used. For obtaining the results for decision tree, C4.5 algorithm was applied and Waikato Environment for Knowledge Analysis (Weka) toolkit was used to experiment the decision tree; in which J48 is java implementation of C4.5. On the other hand, the SAV Genetic Reducer and Johnson Reducer were used for rough set experiments as these are the implementation of Johnson and Genetic algorithms in ROSETTA which is a toolkit for analyzing the data based on rough sets algorithms.

Table T1. Predictive experiments' Results of Both Approaches

Approach	Technique	Role	Prediction Accuracy
Decision Tree	J48	Programmer	58.54
Rough Set	GA	Programmer (22 rules)	70.74
	JA	Programmer (12 rules)	70.74

The table T1 above shows the results and accuracy obtained from training and testing experiments. Johnson Algorithm (JA) technique was finally chosen for programmer role after both approaches were experimented and tested with the techniques mentioned earlier. Even though JA and GA formed the similar results of prediction but the use of JA emerged as more applicable and less complex compared to GA which produced more rules. Besides, prediction accuracy became the basis in selecting the technique which was obtained from testing of experimented results [11][26].

4. Results and Discussion

Gender was considered the scope parameter based on personality type of team member in this study. Therefore, gender and role of team member became the basis in classifying all sets. This led to the fact that personality type of male was different as compared to the female in any software development role [26] as both gender possessed different attitudes and behaviors in the same scope and same type of personality.

A. Descriptive Analysis

This phase discusses the programmer results in descriptive analysis. There were 37 male-programmers and 60 female-programmers and they were set in training dataset in different teams. The findings revealed that only 13 male-programmers were effective and 27 female-programmers appeared in dataset. It should be known here that effective-programmers means that these programmers were extracted from successful developed projects, based on project requirements, and ineffective is another way around. The following figure 1 shows the overall appearance of effective and ineffective programmer appearance in dataset.

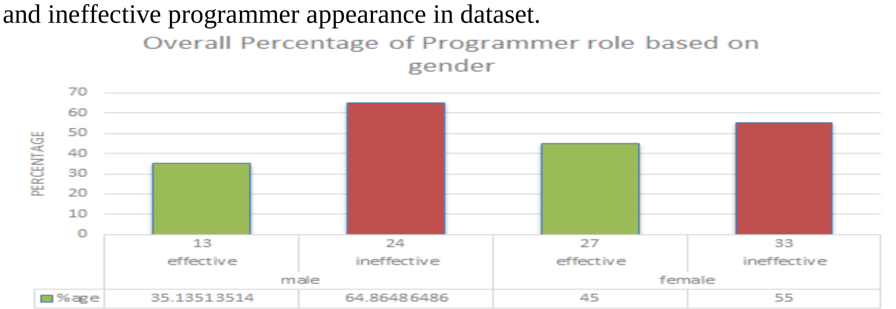

Fig:1. Programmer role by classifying effective and ineffective results

From the graph above, it can be seen that ineffectiveness of male-programmer is 64.86% which is comparatively higher that female-programmer's ineffectiveness with only 55%. Hence, it can be concluded from the above graph that the female-programmer renders comparatively better results than male-programmer in their effectiveness in team composition.

The Programmer's role was also investigated in this section following MBTI pair IE (as discussed earlier in methodology section). Thus, the first pair IE of MBTI showed that the I male-programmers were just 15.4% while the E is strongly effective with 84.6%. Besides, female-programmer's IE traits showed were 40-60%. The first pair of MBTI for the ineffective male-programmer showed the 50-50% for introvert and extrovert traits. Fortunately, appearance in effective-projects for male-programmer is higher for the E trait. Hence, E trait programmer personality was kept aside for male gender programmer. On the other hand, female-programmer's results for I trait in effective-projects was 41% while for ineffective-projects was 36%. In contrast, the E trait for female-programmer in effective projects was 59% while for ineffective-projects was 64%. Even though the significant differences in the rates were not observed but however, I trait was found more favorable for female-programmer than male-programmer.

Table T2. The statistics for considering or eliminating the traits for programmer role

Gender	MBTI traits	Effective %age	Ineffective %age	Considered
Male	I	15.38	50.00	N
	E	84.62	50.00	Y
Female	I	40.74	36.36	Y
	E	59.26	63.64	N

Table T2 above shows the results of effective and ineffective percentage of programmer's role. The effective programmer IE traits were compared one by one by the similar sequence of traits with the ineffective programmer traits (after making classification based on gender). Eventually, the traits were considered only if the appearance of effectiveness was higher than the ineffectiveness.

B. Predictive Analysis

As mentioned earlier, JA algorithm was employed for predictive analysis for its ease and less complexity in use than GA algorithm. This section discusses the rules of programmer and their comparison with descriptive results. This section also discusses the rules of programmer and their comparison with descriptive results. The findings, as showing in the following Table 3, indicated the fact that the JA algorithm produced 12 rules for programmer role whereas GA algorithm produced 22 rules. As only the IE pair of the MBTI was the main focus of this study, therefore only IE possessing rules are discussed below. The following table T3 is representing the rules extracted from JA algorithm for programmer role on IE pair.

Table T3. Decision Rules of Programmer Role based on JA technique

Rule No	Decision Rule	LHS Support	RHS Support	RHS Coverage
1	Gender(2) AND ie(2) => q2(0) OR q2(1)	37	21, 16	0.368421, 0.4
2	ie(2) AND tf(2) => q2(0) OR q2(1)	35	19, 16	0.333333, 0.4
3	ie(2) AND sn(2) => q2(0) OR q2(1)	33	15, 18	0.263158, 0.45
4	ie(1) AND sn(1) AND tf(1) => q2(1) OR q2(0)	13	4, 9	0.1, 0.157895
5	Gender(1) AND ie(1) AND tf(1) AND jp(1) => q2(0) OR q2(1)	9	7, 2	0.122807, 0.05
6	ie(2) AND jp(2) => q2(1) OR q2(0)	8	4, 4	0.1, 0.070175
7	Gender(1) AND ie(1) AND tf(2) => q2(0)	4	4	0.070175
8	Gender(1) AND ie(1) AND jp(2) => q2(0)	3	3	0.052632
9	Gender(2) AND ie(1) AND sn(2) AND tf(1) => q2(1)	1	1	0.025
10	Gender(1) AND ie(2) AND sn(1) AND tf(1) AND jp(1) => q2(0)	1	1	0.017544

The results presented in table T3 were proposed to apply or filter the personality composition based on the effectiveness (i.e., q2 (1)) and ineffectiveness (i.e., q2 (0)) of the rule. From the table T3, it was clearly seen that the first 6 rules were found bi-dimension (i.e., means accuracy is shared with effective and ineffective ends) in results. Furthermore, the effective results from overall 10 IE rules are only 2 rules (see rule number 3 and 9 in table 3) while the ineffective results are 8 rules (see rule number 1,2,4,5,6,7,8 and 10 in table T3).

The rule number 1, 2, 3 and 9 were extracted as effective for programmer based on Right Hand Side (RHS) Support, RHS coverage, and descriptive results. In contrast, rule number 4, 5, 6, 7, 8 and 10 were considered ineffective for programmer under IE pair. From effective dominated rules, the rule number 3 supports the E and N traits for male and female programmers with 55% accuracy and 0.45 coverage of effectiveness. Moreover, female-programmer can be I in personality provided the N and F traits come in the bounding with it. This is supported by rule number 9 whereby even though it has less appearance in dataset but it is effective. Zooming up on the rules number 1 and 2 which are bi-dimension, they possess high accuracy of being ineffective in results but the RHS coverage of being effective is higher than ineffective. Hence, these rules were also considered into the use for team composition. Based from the discussion, it is clearly supported that E, N and F are suitable for both gender programmer but female-programmer can possess I, N, and F.

C. Validation of Rules or Prediction Accuracy

Researchers agreed that the acceptable benchmark for model development is approximately 70%. This is supported by Bakar [36] who stated that model is considered effective if the accuracy reaches up to 70% or above. Moreover, Hvidsten [37] also agreed that 70% is suitable for accuracy and acceptance for modeling results. Therefore, the benchmark accuracy for this study was set on 70% as it is suitable with the sample size as well as the results obtained from Voting with object tracking classifier which achieved the benchmark.

There were 97 members (i.e., 70%) and its testing set contained 41 programmers (i.e., 30%) consisted in the training set of programmer. However, the ineffective results were quite sound in the comparison of effective results due to the situation whereby most of the teams could not achieve the desired results. The programmer rules could achieve 70.73% predictive accuracy when these were experienced with testing set. Nevertheless, this accuracy is acceptable for considering the rules in making decisions. Therefore, in order to obtain the results in percentage form, the results were multiplied with 100.

Table T4. Prediction Accuracy Table for Programmer Role

		PREDICTED		
ACTUAL		0 (ineffective)	1 (effective)	(*100)
	0(ineffective)	29	3	90.625%
	1 (effective)	9	0	0%
	(*100)	76.3158%	0%	70.7317% (Accuracy)

From table T4 which shows the prediction accuracy for programmer role, 29 ineffective results were predicted accurately and 9 were wrongly predicted for ineffective results. Meanwhile, effective results were very low recorded in the testing set (i.e., only 9 effective records in testing set).

D. Prediction Accuracy Validation with Industrial Data

The results obtained from this study were sufficient enough to make the rules acceptable but, however, it leaves the general acceptance. This is because, the results were only extracted and validated from the academic sample. So, one can claim and show the constraints of sample of students' maturity on professional behaviours. Hence, this study also validated the rules with industrial data which were extracted from academic data.

Briefly explained, the validation of predictor rules with industrial data was dealt with the same way as it was conducted from testing set (i.e., 30% from academic data). In addition, the accuracy with industrial dataset was also found by using the classification technique of "Voting with object tracking". Moreover, the industrial dataset was composed of three different companies with 12 teams and 52 size sample obtained for programmer role which is even higher than the academic testing set.

Table T5.Predication Accuracy Validation of Programmer Role from Data

Academic Accuracy	Industrial Accuracy	Overall Accuracy
70.73%	71.15%	70.94%

The industrial dataset with 52 sample size obtained 71.15% of prediction accuracy while academic testing set with 41 sample size obtained 70.73%. As a result, the overall accuracy from academic and industrial datasets was 70.94% and it met the benchmark of the study.

5. CONCLUSION

The overall findings of this study confirmed the fact that maturity of age does influence the personality types, but however, it remains constant throughout the life [38]. Hence, results obtained from academic sample can also be generalized for industrial practices. The first and descriptive part of this study found the general appearance of the traits in composition of team based on personality. But, the predictive part produced analytical touch in the first part of the study for gaining its wider side.

Descriptive part was employed to determine the IE traits by calculating their frequency and descriptive analysis. The findings revealed that particular trait can only be proposed for team composition provided its appearance is higher in effective projects' results. Moreover, the trait having less effective projects' result was eliminated from the team composition. Since the present study emphasised gender as the base of classification, therefore sheer different results were obtained. For instance, male-programmers emerged as the most suitable and adjustable with E trait while female-programmer showed effectiveness working with I trait's composition.

Moreover, the findings of predictive part of the study supported the general consent of the descriptive part in detail. As only IE personality traits are highlighted to consider or eliminate for programmer role in descriptive part, but, predictive part also brought into other traits with IE to choose particular trait at certain conditions. For instance, female-gender could produce the quality results if the I trait is composed with intuitive (N) and thinking (T). This finding supported and proposed rule number (1, 2, 3, and 9 from table T3, given above,) to use for effective team composition. But, the rest of rules (i.e., 4, 5, 6, 7, 8, and 10 from table T3 given above) failed to produce the assurance of effectiveness in team formation.

Finally, the prediction accuracy was measured to check the validation of the rules proposed for selecting a programmer in team. Voting with object tracking technique was applied on academic and industrial datasets. To evaluate the efficiency of rules, 70% was kept as the benchmark for acceptable accuracy. However, the results obtained 70.94% overall accuracy that includes 70.73% accuracy from academic data and 71.15% from industrial data. Based on these results, this study claims that the results can be safely implemented to compose an effective team with programmer role.

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