On the Relationship of Emotional Intelligence and Group Work Results of University Students

Project Report

By

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Abstract

This is an attempt to replicate and extend the analyses done on 'The Relationship of Emotion Intelligence and Group Work Result' by Thu Hang Le, Minh Ngoc Pham, Pham Phuong Anh Nguyen, and Linh Thi Phuong Nguyen.

The goal of this study is to investigate the relationship between Emotional Intelligence and Group Work results of university students. This report provides a summary of the methods and techniques we used to complete this project, and an analysis conducted using these techniques on data collected from students at Indian universities.

Contents

Introduction

Working in groups offers a variety of advantages for students because this method promotes higher-level thinking, satisfies students with the learning experience in a higher level of communication to improve self-management, making work plans, and help them understand the feelings of others [1]. Therefore, many documents confirm the benefits of group working for university students [2].

Firstly, teamwork allows students to perform work related to applying knowledge, using expertise to solve a single problem [3], [4].

Secondly, students have the opportunity to experiment and acquire new skills they need in the future. Some skills include problem-solving, friendly competition, relationship developing, personal qualities, and creating motivation [5].

Thirdly, a positive impact of teamwork has been shown on student achievement, motivation, and attitudes toward learning [6], [7].

According to research by Gujral and Ahuja [8], the authors affirm that Emotional Intelligence (EI) plays an important role in how team members collaborate and cooperate on the same task. At the same time, EI has a direct impact on the students' group work results in the educational environment. Besides, research by Lin [9], Bock et al. [10] shows that EI has an influence on knowledge sharing ability. Individuals with high EI will easily meet the requirements such as creating, enforcing equity, and deploying exchanges among other team members.

With the above analysis, this study focuses on solving the following goal: to study EI's direct relationship with student group work results.

Chapter 1

Techniques Used

1.1 Cronbach's Alpha Reliability Test

Cronbach's alpha is a reliability coefficient that provides a method of measuring internal consistency of tests and measures.

In order to use Cronbach's alpha as a reliability coefficient, the data from the measure must satisfy the following conditions:

1. Normally Distributed and Linear
2. Tau-equivalence
3. Independence between Errors

Cronbach's alpha is calculated by taking the score from each scale item and correlating them with the total score for each observation and then comparing that with the variance for all individual item scores. Cronbach's alpha is best understood as a function of the number of questions or items in a measure, the average covariance between pairs of items, and the overall variance of the total measured score.

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_{y_i}^2}{\sigma_x^2}\right)$$

k : the number of items in the measure

$\sigma_{y_i}^2$: variance associated with each

σ_x^2 : variance associated of the total scores

Cronbach's alpha	Reliability Level
<0.5	Unacceptable
0.5-0.6	Poor
0.6-0.7	Questionable
0.7-0.8	Acceptable
0.8-0.9	Good
>0.9	Excellent

If alpha is too high (>0.95) it may suggest that some items are redundant as they are testing the same question but in a different guise. A maximum alpha value of 0.90 has been recommended.[23]

1.2 Exploratory Factor Analysis (EFA)

In multivariate statistics, exploratory factor analysis (EFA) is a statistical method used to uncover the underlying structure of a relatively large set of variables. EFA is a technique within factor analysis whose overarching goal is to identify the underlying relationships between measured variables. It serves to identify a set of latent constructs underlying a battery of measured variables.

EFA is based on the common factor model. In this model, observed variables are expressed as a function of common factors, unique factors, and errors of measurement. Each unique factor influences only one observed variable, and does not explain correlations between observed variables.

There are a number of procedures designed to determine the optimal number of factors to retain in EFA. The following two tests are usually used to measure if the data is adequate to proceed with EFA.

Bartlett's test of sphericity

This test verifies the hypothesis that variables are not correlated in the population. Therefore, the null hypothesis is that the correlation matrix is equal to an identity matrix. If the correlation matrix is equal to an identity matrix, we cannot proceed with EFA, since there is no correlation between variables. The statistical analysis behind this test goes as follows:

$$\chi^2 = -\left[(n-1) - \frac{2v+5}{6}\right] \ln|R|$$

n : sample size

v : number of variables

$|R|$: determinant of the correlation matrix

In the literature, we can see that if the level of significance equals $p < 0.05$ that means we can proceed with EFA.

Kaiser-Meyer-Olkin (KMO)

The test verifies if the inverse correlation matrix is close to a diagonal matrix, comparing the values of linear correlations with values of partial correlations. It is conducted to examine the partial correlation between the variables.

$$KMO = \frac{\sum\sum_{j \neq k} r_{jk}^2}{\sum\sum_{j \neq k} r_{jk}^2 + \sum\sum_{j \neq k} p_{jk}^2}$$

r_{jk} : correlation coefficient between X_j and X_k

p_{jk} : correlation coefficient between X_j and X_k, controlling for other Xs.

KMO	Quality
<0.5	Unacceptable
0.5-0.7	Mediocre
0.7-0.8	Good
0.8-0.9	Great
>0.9	Excellent

Once the above tests confirm the appropriateness of the data, we are ready to find the number of factors.

To retain factors, the following methods are used:

1. **Kaiser criterion**: It proposes if a factor's eigenvalue is above 1.0, we should retain that factor. The logic behind it is: if a factor has an eigenvalue = 3.0, that means that the factor explains the same amount of variance as 3 items.

2. **Scree plot**: Here, we evaluate when there is a substantial decline in the magnitude of the eigenvalues. This method also has some limitations, because it can generate ambiguous results and are open to subjective interpretation.

3. **Parallel analysis**: The eigenvalue of the sample and eigenvalue of random data are calculated. The number of factors is selected when the number of eigenvalues of real data is bigger than from simulated data. This method usually works well.

Simulated matrix for Parallel Analysis

The Monte Carlo method

Monte Carlo methods are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. The underlying concept is to use randomness to solve problems that might be deterministic in principle. They are often used in physical and mathematical problems and are most useful when it is difficult or impossible to use other approaches. Monte Carlo methods are mainly used in three problem classes: optimization, numerical integration, and *generating draws from a probability distribution.*

The general idea behind Horn's Parallel Analysis is that, "If m sets of very large samples of size N are drawn independently from a normally distributed population of random numbers and the resulting m "variables" are intercorrelated, it is to be expected that the $m \times m$ matrix of correlation coefficients, R, will approximate an identity matrix." J. L. Horn [26].

In Parallel Analysis, we first simulate data of the same dimensions as we have in our sample using the normal distribution with parameters equal to our sample parameter estimates. We then get the correlation matrix, and compute the eigenvalues of this matrix.

To reduce the effect of potential outliers, this process is repeated several hundred times, and the mean is considered (The first eigenvalue is the mean of the set of eigenvalues with the highest magnitude in each iteration, the second eigenvalue is the mean of the set of eigenvalues with the second highest magnitude in each iteration, and so on).

Now, this final set of eigenvalues is plotted on the scree plot, and the number of eigenvalues of our actual data correlation matrix above this plot of eigenvalues is the number of factors that should be retained.

1.2.1 Factor scores

After an appropriate factor solution has been established, one may wish to calculate factor scores by using the factor loadings and factor correlations. Conceptually, a factor score is the score that would have been observed for a person if it had been possible to measure the factor directly.

A frequently used method of estimating refined factor scores is Thurstone's (1935) least squares regression approach, although several other strategies have been developed (e.g., Bartlett, 1937; Harman, 1976; McDonald, 1981). Most statistical software packages provide options to compute refined factor scores by one or more of these methods.

In the majority of instances, refined factor scores have less bias than coarse factor scores and thus are favoured over coarse factor scores as proxies for the factors (Grice, 2001). However, a complicating issue in factor score estimation is the indeterminate nature of the common factor model. With respect to factor scores, this indeterminacy means that an infinite number of sets of factor scores can be computed from any given factor analysis that will be equally consistent with the same factor loadings (Grice, 2001).

The degree of indeterminacy depends on several aspects, such as the ratio of items to factors and the size of the item communalities (e.g., factors defined by several items with strong communalities have better determinacy). If a high degree of indeterminacy is present, the sets of factor scores can vary so widely that an individual ranked high on the dimension in one set may receive a low ranking on the basis of another set. In such scenarios, the researcher has no way of discerning which set of scores or rankings is most accurate

In our project, we have used Bartlett's least square regression approach.

In EFA, the following model (Timothy A. Brown [27]) is used:

$$y_j = \lambda_{j1}\eta_1 + \lambda_{j2}\eta_2 + ... + \lambda_{jm}\eta_m + \epsilon_j$$

Where y_j is the $j-th$ observed variable, $\eta_1, \eta_2, ..., \eta_m$ are the latent variables, and ϵ_j is the error terms and $\lambda_{j1}, \lambda_{j2}, ..., \lambda_{jm}$ are the corresponding factor loadings.

1.3 Confirmatory Factor Analysis (CFA)

In statistics, confirmatory factor analysis (CFA) is a special form of factor analysis, most commonly used in social science research. It is used to test whether measures of a construct are consistent with a researcher's understanding of the nature of that construct (or factor). As such, the objective of confirmatory factor analysis is to test whether the data fit a hypothesized measurement model.

In CFA, we theorise the path diagram model between the observed variables and the latent variables. The following model (Timothy A. Brown [27]) is used :

$$\begin{aligned} O_{1j} &= \lambda_1\eta_j + \epsilon_1 \\ O_{2j} &= \lambda_2\eta_j + \epsilon_2 \\ &\vdots \end{aligned}$$

where $O_{1j}, O_{2j}, ...$ are observed variables theorised to be dependent on the latent variable η_j and $\epsilon_1, \epsilon_2, ...$ are the error terms and $\lambda_1, \lambda_2, ...$ are the factor loadings.

In CFA, the following absolute data fit indices are used to determine how well the model fits the data:

Absolute fit indices

Absolute fit indices determine how well the a priori model fits, or reproduces the data. Absolute fit indices include, but are not limited to, the Chi-Squared test, RMSEA, GFI, AGFI, RMR, and SRMR.

<u>Chi-squared test</u>

The chi-squared test indicates the difference between observed and expected covariance matrices. Values closer to zero indicate a better fit; smaller difference between expected and observed covariance matrices. Chi-squared statistics can also be used to directly compare the fit of nested models to the data. One difficulty with the chi-squared test of model fit, however, is that researchers may fail to reject an inappropriate model in small sample sizes and reject an appropriate model in large sample sizes. As a result, other measures of fit have been developed.

<u>Root Mean Square Error of Approximation</u>

The root mean square error of approximation (RMSEA) avoids issues of sample size by analysing the discrepancy between the hypothesized model, with optimally chosen parameter estimates, and the population covariance matrix. It can be interpreted as the square root of population misfit per degree of freedom. The RMSEA ranges from 0 to 1, with smaller values indicating better model fit. A value of 0.06 or less is indicative of acceptable model fit.

$$RMSEA = \sqrt{\max\left\{\frac{(\chi^2/df)-1}{n-1}, 0\right\}}$$

Root Mean square Residual and Standardized Root Mean square Residual

The root mean square residual (RMR) and standardized root mean square residual (SRMR) are the square root of the discrepancy between the sample covariance matrix and the model covariance matrix. The RMR may be somewhat difficult to interpret, however, as its range is based on the scales of the indicators in the model (this becomes tricky when you have multiple indicators with varying scales; e.g., two questionnaires, one on a 0–10 scale, the other on a 1–3 scale). The standardized root mean square residual removes this difficulty in interpretation, and ranges from 0 to 1, with a value of 0.08 or less being indicative of an acceptable model.

Goodness of Fit Index and Adjusted Goodness of Fit Index

The goodness of fit index (GFI) is a measure of fit between the hypothesized model and the observed covariance matrix. It is the proportion of variance accounted for by the estimated population variance. GFI is analogous to the R^2 statistic.

The adjusted goodness of fit index (AGFI) corrects the GFI, which is affected by the number of indicators of each latent variable. The GFI and AGFI range between 0 and 1, with a value of over 0.9 generally indicating acceptable model fit.

$$GFI = 1 - \frac{\operatorname{tr}\left(\hat{\Sigma}^{-1}S - I\right)^2}{\operatorname{tr}\left(\hat{\Sigma}^{-1}S\right)^2}$$

$$AGFI = 1 - \tfrac{1-GFI}{P}, \text{ where } P = \left(\tfrac{2df_T}{k(k+1)}\right)$$

Relative fit indices

Relative fit indices (also called "incremental fit indices" and "comparative fit indices") compare the chi-square for the hypothesized model to one from a "null", or "baseline" model. This null model almost always contains a model in which all the variables are uncorrelated, and as a result, has a very large chi-square (indicating poor fit). Relative fit indices include the normed fit index and comparative fit index.

Normed Fit Index and Non-Normed Fit Index

The normed fit index (NFI) is a relative measure of the difference between the chi-squared value of the hypothesized model and the chi-squared value of the null model. However, NFI tends to be negatively biased.

The non-normed fit index (NNFI; also known as the Tucker–Lewis index, as it was built on an index formed by Tucker and Lewis, in 1973) resolves some of the issues of negative bias, though NNFI values may sometimes fall beyond the 0 to 1 range. It is the NFI adjusted for degrees of freedom, and is a better test for smaller samples. Values for both the NFI and NNFI should range between 0 and 1, with a cutoff of 0.95 or greater indicating a good model fit.

$$NFI = 1 - \frac{\chi^2_{null}}{\chi^2_{proposed}}$$

$$NNFI = \frac{\chi^2/df_{null} - \chi^2/df_{proposed}}{\chi^2/df_{null} - 1}$$

Comparative Fit Index

The comparative fit index (CFI) analyses the model fit by examining the discrepancy between the data and the hypothesized model, while adjusting for the issues of sample size inherent in the chi-squared test of model fit, and the normed fit index. It is a revised version of NFI, and it is not very sensitive to sample size.

CFI values range from 0 to 1, with larger values indicating better fit. Previously, a CFI value of 0.90 or larger was considered to indicate acceptable model fit. However, recent studies have indicated that a value greater than 0.90 is needed to ensure that misspecified models are not deemed acceptable. Thus, a CFI value of 0.95 or higher is presently accepted as an indicator of good fit.

$$CFI = 1 - \frac{\chi^2_{proposed} - df_{proposed}}{\chi^2_{null} - df_{null}}$$

Parsimonious Fit Indices (PGFI, PNFI)

The "Law of Parsimony" is a scientific principle which suggests that when there are multiple competing hypotheses for a certain physical or observable phenomenon, the simplest explanation is more likely to be the correct one.

Parsimony-corrected fit indices are relative fit indices that are adjustments to most of the fit indices mentioned above. The adjustments are to penalize models that are less parsimonious, so that simpler theoretical processes are favoured over more complex ones. The more complex the model, the lower the fit index. Parsimonious fit indices include PGFI (based on the GFI), PNFI (based on the NFI).

$$PGFI = GFI \times P$$

$$PNFI = NFI \times P, \text{ where } P = \left(\tfrac{2df_T}{k(k+1)}\right)$$

n : sample size, χ^2 : chi-square value for model, df : degrees of freedom for model, k : number of observed variables, $\hat{\Sigma}$: predicted covariance matrix based on model, S : sample covariance matrix, χ^2_{null} : chi-square for null model, $\chi^2_{proposed}$: chi-square for proposed model, tr : trace.

1.3.1 Indicators of convergent validity

In general, convergent validity is the degree to which, two measures which are theoretically related, are indeed related. In our specific instance, convergent validity is the degree of confidence we have that a factor is well-measured by its fit indices.

We have the following indicators of convergent validity:

- Standardized Estimates: It predicts how much the observed variables change in standard deviation for unit change of standard deviation in the corresponding latent variable. It is computed for each observed variable.

- Average Variance Extracted(AVE): It is a measure of the amount of variance that is captured by a latent variable in relation to the amount of variance due to measurement error. For adequate convergence of factor loadings, $AVE > 0.5$.

$$AVE = \frac{\sum \lambda_i^2}{n}$$

  where λ_i are factor loadings of item i and n is the number of items.

- Composite Reliability(CR): It is a measure of the internal consistency of the observed variables loading on the latent variables. $CR > 0.7$ implies a good model.

$$CR = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum Var(\epsilon_i)}$$

  where λ_i are factor loadings and ϵ_i is error of item i

If our values for the fit indices and the indicators of convergent validity are in the appropriate ranges, then we can conclude that our model is indeed a good fit for our data.

1.4 Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) refers to the diverse set of methods used by scientists to construct a model to represent how various aspects of an observable or theoretical phenomenon are thought to be causally structurally related to one another.

Structure Equation Modeling is typically used for confirmatory factor analysis. In this report, `lavaan` package in R has been used to assess the proposed measurement model in a structural equation model.

1.5 Regression Analysis

Regression analysis is a statistical method that shows the relationship between two or more variables. Usually expressed in a graph, the method tests the relationship between a dependent variable against independent variables. Typically, the dependent variable(s) changes with the independent variable(s) and the regression analysis attempts to answer which factors matter most to that change.

A positive slope implies a positive relationship between the variables. A negative slope implies a negative relationship between the variables. No conclusion can be drawn in case of a zero slope.

Chapter 2

Original Paper

2.1 Method of Data Collection

To collect accurate data, the author of the paper (Thu Hang Le et al. [28]) went directly to universities (National Economics University, Banking Academy, University of Economics – National University, Foreign Trade University, Academy of Finance, University of Commerce) in Hanoi to distribute and collect survey questionnaires from July to October 2020. The initial emotional intelligence scale consisted of 33 items was designed based on the definition of Mayer and Salovey [3], Ghuman [4] and the original questionnaire by Shutte et al. [1]. A preliminary quantitative study with 20 students to check the reliability of the scales and items was done before conducting the survey on a large scale. The scale of teamwork results includes 6 items was proposed by Volet and Mansfield[29]. The author asked each university to send a list of 150 students. Then, the author randomly selected 60–70 students from each university based on the list and made an appointment to meet in a lecture hall of the university itself. Each student took about 15 min to complete the survey. Total number of questionnaires distributed was 385 questionnaires, the number of questionnaires collected was 380, the number of questionnaires collected after cleaning was 372, estimated at 96.6 %.

The survey questionnaire is divided into 2 parts: the first part to find out how respondents felt about emotional intelligence and teamwork performance; the second part explores personal information such as gender, what year students are from, and how often they work in teams. The survey was designed with 27 items, of which 3 items were about the characteristics of the respondents, the remaining 24 items were designed on a 5-point Likert scale (1: Strongly disagree; 2: Disagree; 3: Neutral; 4: Agree; 5: Strongly agree), focusing on 2 factors: (1) emotional intelligence; (2) teamwork performance. The questionnaire was only valid when fully filled in both parts of the questionnaire. After removing invalid questionnaires, the final dataset contains 372 questionnaires. Based on the data set, further research can study the direct effects of emotional intelligence on teamwork performance of university students and give some recommendations to managers, lecturers, and university students to promote teamwork performance of university students in Vietnam.

2.2 Literature Review and Research Framework Introduction

The items used in the questionnaire has been explained below:

A. Relationship between EI and Group Work Results

1. Emotion Intelligence (EI)

Emotion Intelligence (EI) has been a research topic of particular that interests many scholars over the past decades, rooted in Gardner's theory of multiple intelligence (1983). Goleman [15] defined EI as the understanding of emotion on one's own and that of others and using them in decision-making. Mayer and Salovey [16] defined EI as "The ability to accurately perceive, evaluate and express emotions; the ability to reach and/or create emotions when they think; ability to understand emotions and knowledge about emotions; and the ability to regulate emotions to promote emotional and intellectual development".

2. EI model

The conceptual framework that underpins this study is based on the work of Mayer and Salovey [16] concerning the four branches of the EI model:

1. Emotional Awareness
2. Emotion's Usage
3. Emotional Understanding
4. Emotional Control

Emotional Awareness is understood as the ability to self-perceive the emotions of self and that of others accurately.

Emotion's Usage is defined as the ability to use one's emotions to promote thinking, thinking, and awareness about mood swings, leading to consideration of alternative attitudes and understanding about a change in state by using emotions to solve problems.

Emotional Understanding is the ability to help individuals understand emotions, causes, and development of emotions, including the ability to define, distinguish types of emotions, understand the complexity of emotions as well as patterns. emotionally: loss often entails boredom, anger removes fear, etc.

Emotional Control is the capability for the individual to control their own emotions and organize his emotions. Previous studies have confirmed the relationship between the success of group work and EI [17], [18], Muhammad including improvement of communication [19] which increase the value of team productivity [20], increase collaboration to achieve common goals [8], provide opportunities for students to reflect and well-applied teamwork skills while doing practical exercises [19].

Hypothesis 1 (H1): Emotion Intelligence has a positive influence on student group work results.

2.3 Data Analysis

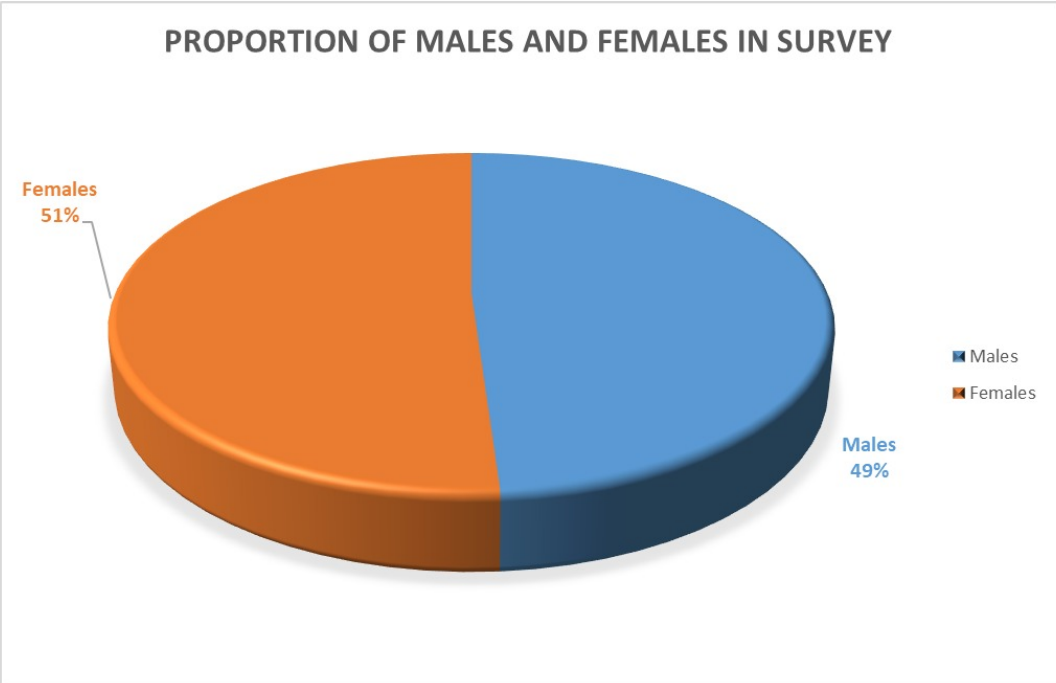
A. Survey

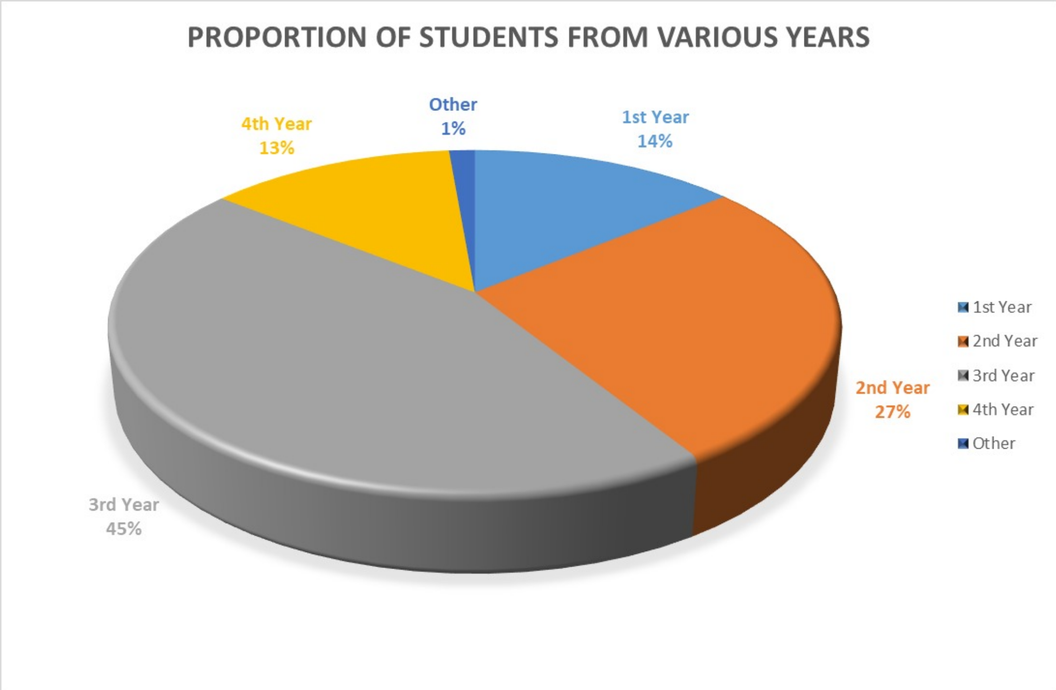
The authors inherit the scale from previous studies to build questionnaires and distribute them from July to October 2020 for 6 universities with economic majors in Hanoi. The survey questionnaire was distributed and collected 372 valid responses.

The characteristics of the sample has been described in Table I:

Table I : Characteristics of Sample

Demographic Information	Frequency	Number of Respondents	Percentage (%)
Gender	Female	183	49.2
	Male	189	50.8
Year of Students	1st	52	14.0
	2nd	101	27.2
	3rd	166	44.6
	4th	48	12.9
	Other	5	1.3
Frequency of Group Working	Never	2	0.5
	Rarely	10	2.7
	Sometimes	96	25.8
	Usually	264	71.0





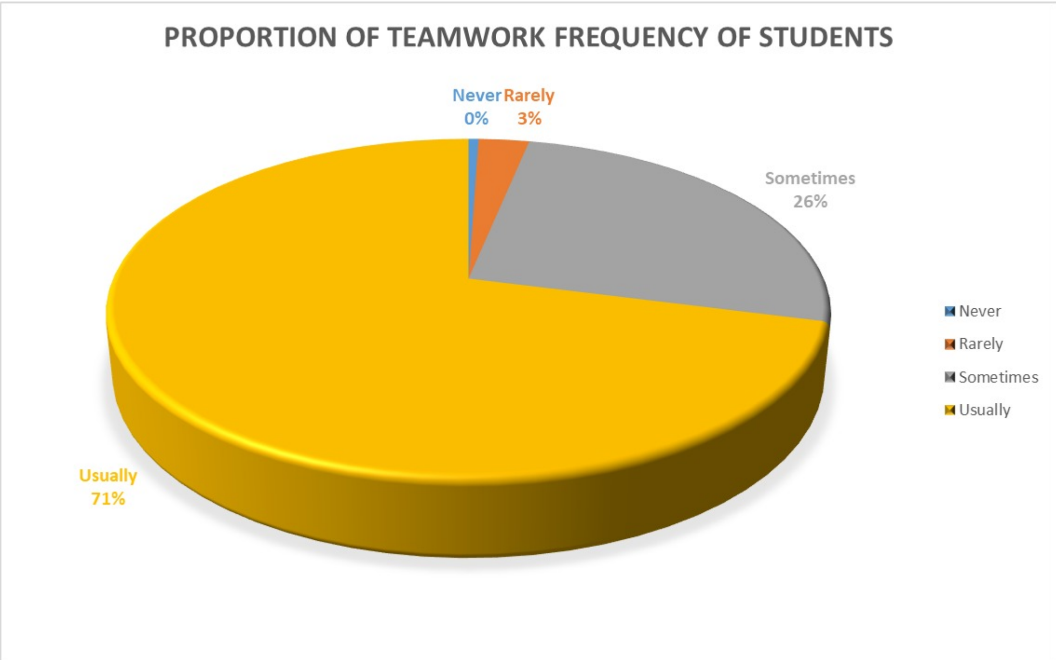


Fig. 2.1: Profile of the Respondents

B. Measures

All scales used in the research inherits from previous studies. The scales will be evaluated based on the Likert scale (1 – strongly disagree, 2 – disagree, 3 – neutral, 4 – agree, and 5 – strongly agree).

Emotional Intelligence (EI): The 18-item scale is developed by the research teams Mayer-Salovey [16], BarOn [21], and Goleman [22]. Emotional Awareness (EA), Emotion's Usage (EU), Emotional Understanding (EUS) and Emotional Control (EC).

- **Emotional Awareness** (EA): includes 5 items, such as a self-assessment sample, “I am aware of personal emotions (happy, annoying, nervous, . . .)when meeting someone”.
- **Emotional Understanding** (EUS): includes 5 items, for example, self-assessment sentence, “When communicating, I know how to organize event content to make listeners feel comfortable”.
- **Emotional Usage** (EU): includes 5 items, for example, the self-assessment sentence pattern, “My ability to think of new ideas is influenced by my mood (from sad to happy, there are more new ideas or vice versa)”.
- **Emotional Control** (EC): includes 3 items, such as self-assessment sentence pattern, “I can always control my emotions in all situations”.
- **The results of the group work** (R): designed by Callin and Bamford [20] yield 6 evaluation sentences, such as, “The team worked together to complete tasks in a timely manner”.

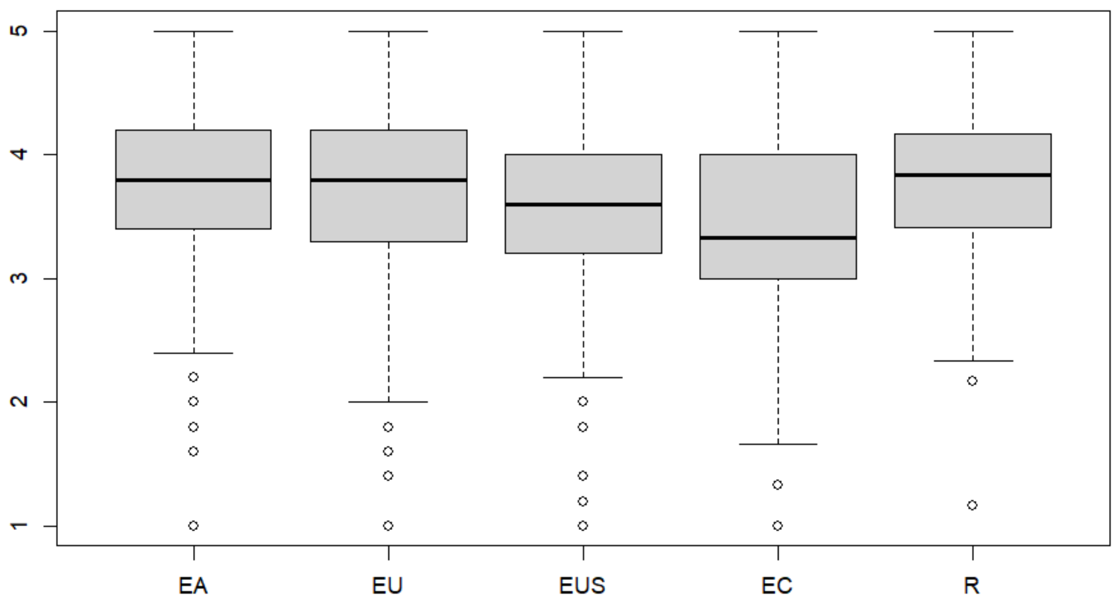


Fig. 2.2: Boxplot of the Scales

Table II: Characteristics of Variables

Variables	Mean	SD	Skewness	Excess Kurtosis
Emotional Awareness (EA)	**3.792**	**0.644**	**-0.505**	**1.012**
EA1	4.062	0.830	-0.909	1.162
EA2	3.753	0.751	-0.479	0.530
EA3	3.677	0.803	-0.104	-0.331
EA4	3.726	0.847	-0.167	-0.357
EA5	3.742	0.758	-0.462	0.455
Emotional Usage (EU)	**3.731**	**0.689**	**-0.710**	**1.117**
EU1	3.995	0.863	-0.646	0.324
EU2	3.720	0.997	-0.546	-0.085
EU3	3.626	1.021	-0.435	-0.420
EU4	3.473	0.897	-0.424	-0.012
EU5	3.839	0.961	-0.624	0.042
Emotional Understanding (EUS)	**3.563**	**0.763**	**-0.442**	**0.235**
EUS1	3.651	0.991	-0.571	0.038
EUS2	3.497	0.930	-0.294	-0.255
EUS3	3.473	0.861	0.020	-0.291
EUS4	3.696	0.900	-0.365	-0.294
EUS5	3.497	0.904	-0.354	-0.102
Emotional Control (EC)	**3.472**	**0.800**	**-0.461**	**0.287**
EC1	3.446	0.999	-0.380	-0.234
EC2	3.543	0.918	-0.483	0.179
EC3	3.427	0.813	-0.383	0.236
Teamwork Result (R)	**3.753**	**0.565**	**-0.407**	**0.812**
R1	3.927	0.702	-0.413	0.551
R2	3.742	0.733	-0.421	0.556
R3	3.734	0.761	-0.249	0.170
R4	3.715	0.794	-0.515	0.285
R5	3.780	0.681	-0.362	0.545
R6	3.621	0.635	-0.049	-0.217

2.3.1 Cronbach's Test

We wish to measure the reliability of the data using Cronbach's alpha coefficient. However, as noted in Cronbach's Alpha Reliability Test, the data must be normally distributed. We have used R software to plot the data and compare with the corresponding normal densities. Further, we have used quantile-quantile comparison with the corresponding normal distributions.

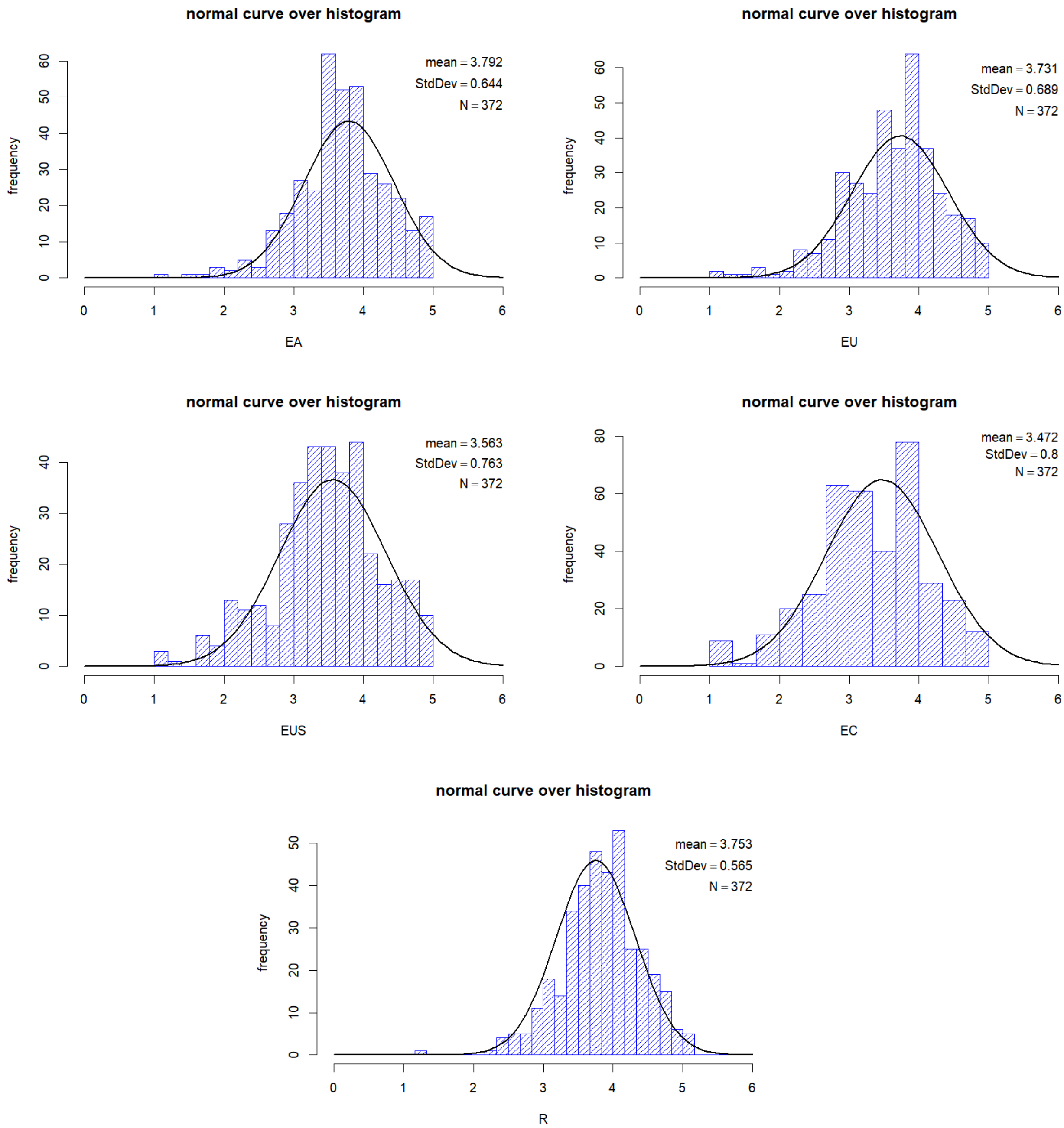


Fig. 2.3: Histograms with Normal Density Plot

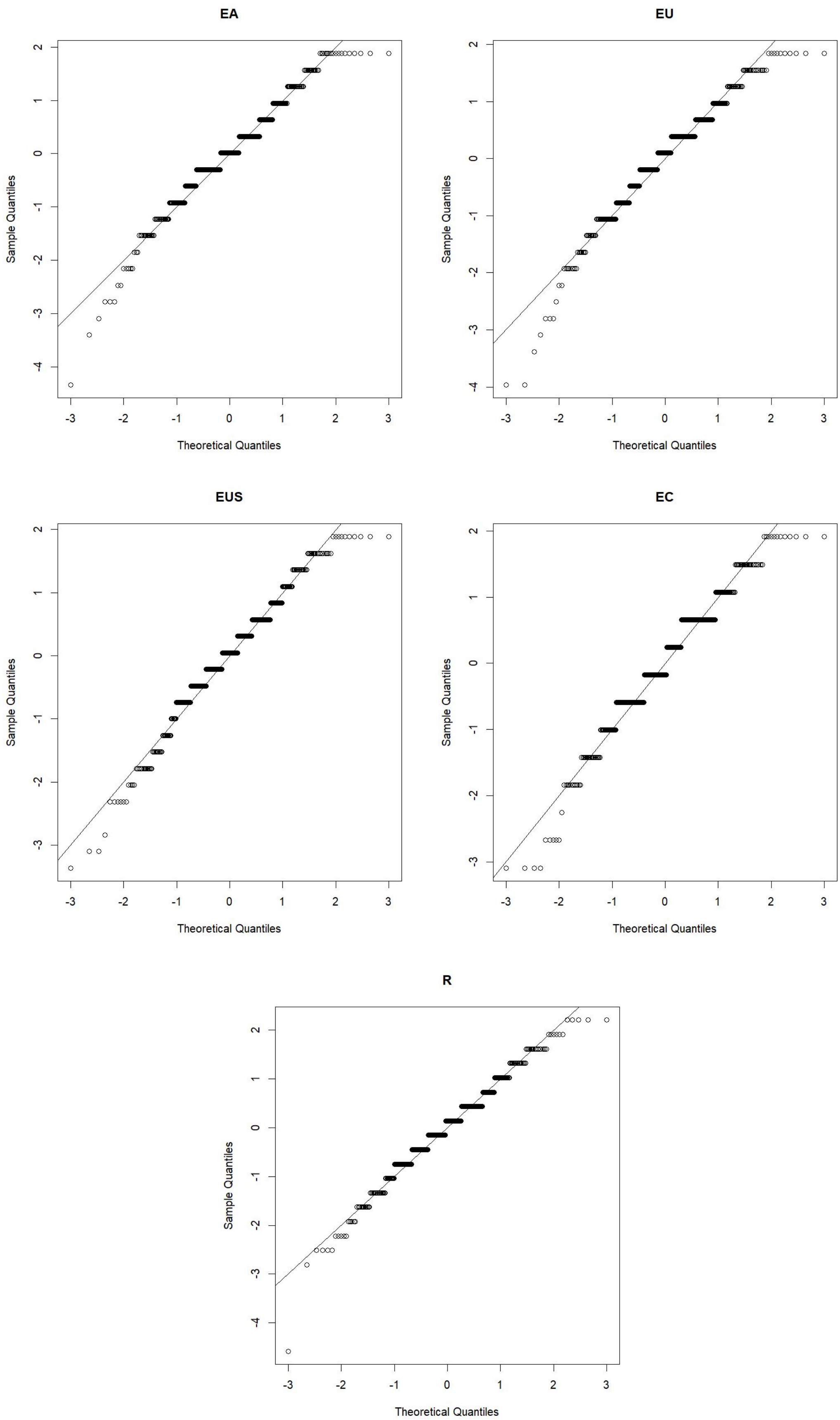


Fig. 2.4: Q-Q plot Comparison

It follows from these comparisons that the data is normally distributed. Hence, Cronbach's Alpha Reliability Test can be performed on the data.

Table III: Cronbach's Alpha Values

Item	Cronbach's α
EA	0.865
EU	0.776
EUS	0.888
EC	0.849
R	0.876

As all values of α are greater than 0.7, the data has an acceptable level of reliability. We conclude that the data is appropriate for Factor Analysis.

2.3.2 Correlation Matrix

The correlation matrix of the variables show how correlated the variables are with each other. The heat map of the correlation matrix of the data is given below:

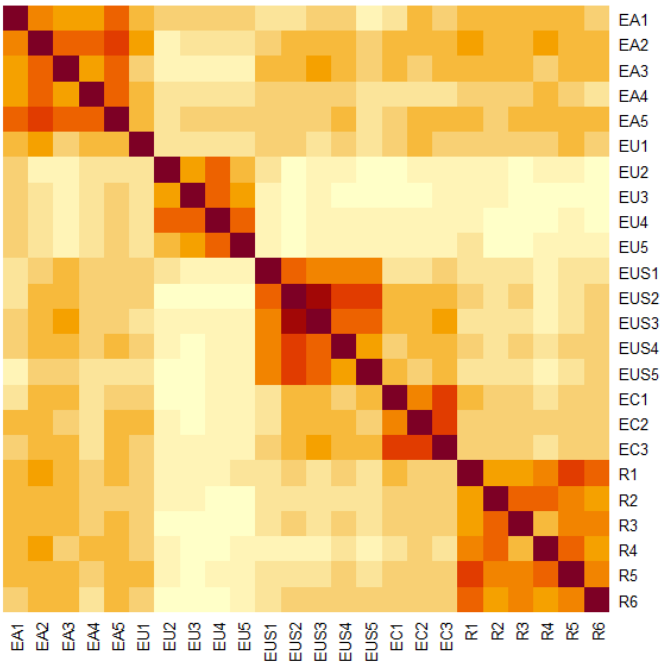


Fig. 2.5: Heat Map of Correlation Matrix

2.3.3 Exploratory Factor Analysis

First, we conduct Bartlett's test of sphericity to check whether the variables are correlated. This is done using the `cortest.bartlett()` function from the `psych` package in `R`.

We get that p-value $= 0 < 0.05$, so we can conclude from Bartlett's test that the variables are indeed correlated.

Next we will perform the KMO (Kaiser-Meyer-Olkin) test using the `KMO()` function of the `psych` package in `R`, which gives $KMO = 0.89 > 0.5$.

Next, we see that the cumulative variance = 59% $\geq$50%.

Hence, we can proceed with Exploratory Factor Analysis.

We will now try to extract the number of factors using Parallel Analysis and select which factors to retain using `fa.parallel()` function in `psych` package in `R`.

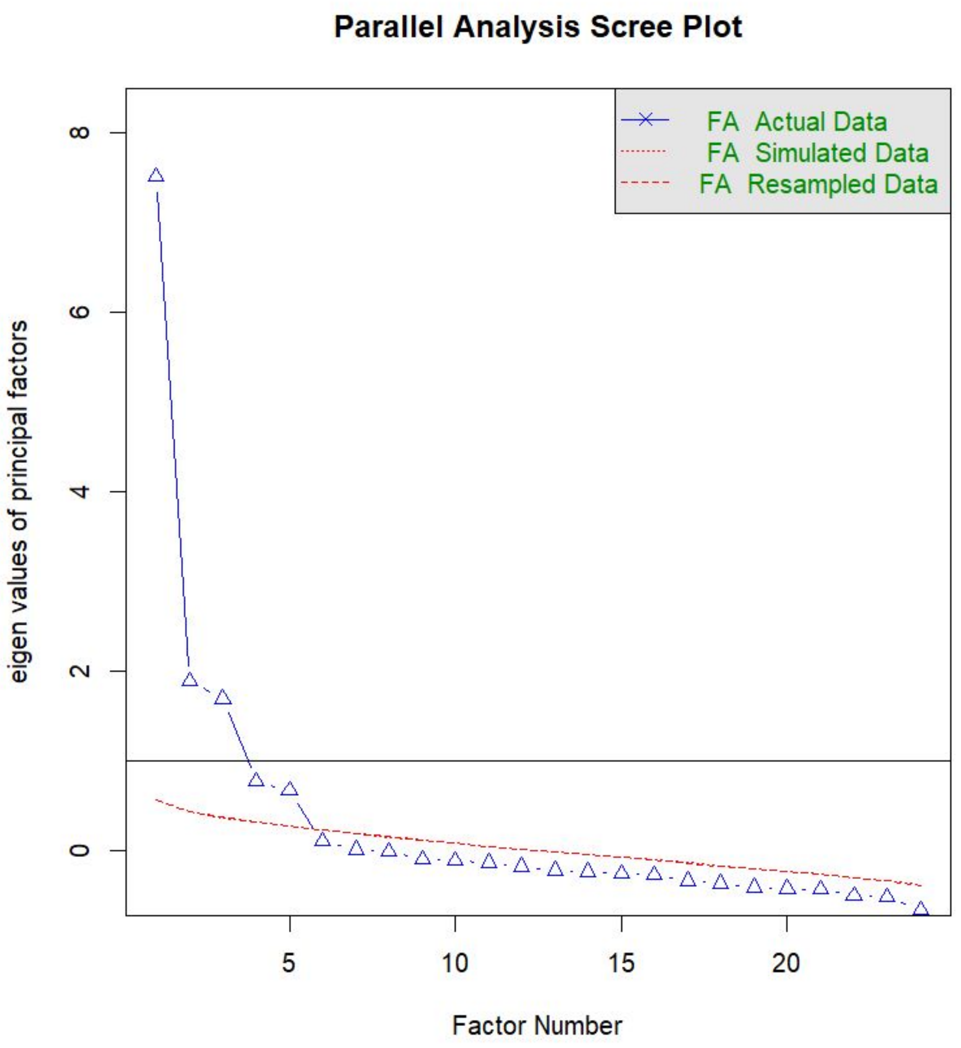


Fig. 2.6: Scree Plot

The red line represents the eigenvalues obtained from the Simulated Matrix generated by Monte Carlo method.

From the Parallel Analysis, we can see that we need to retain 5 factors.

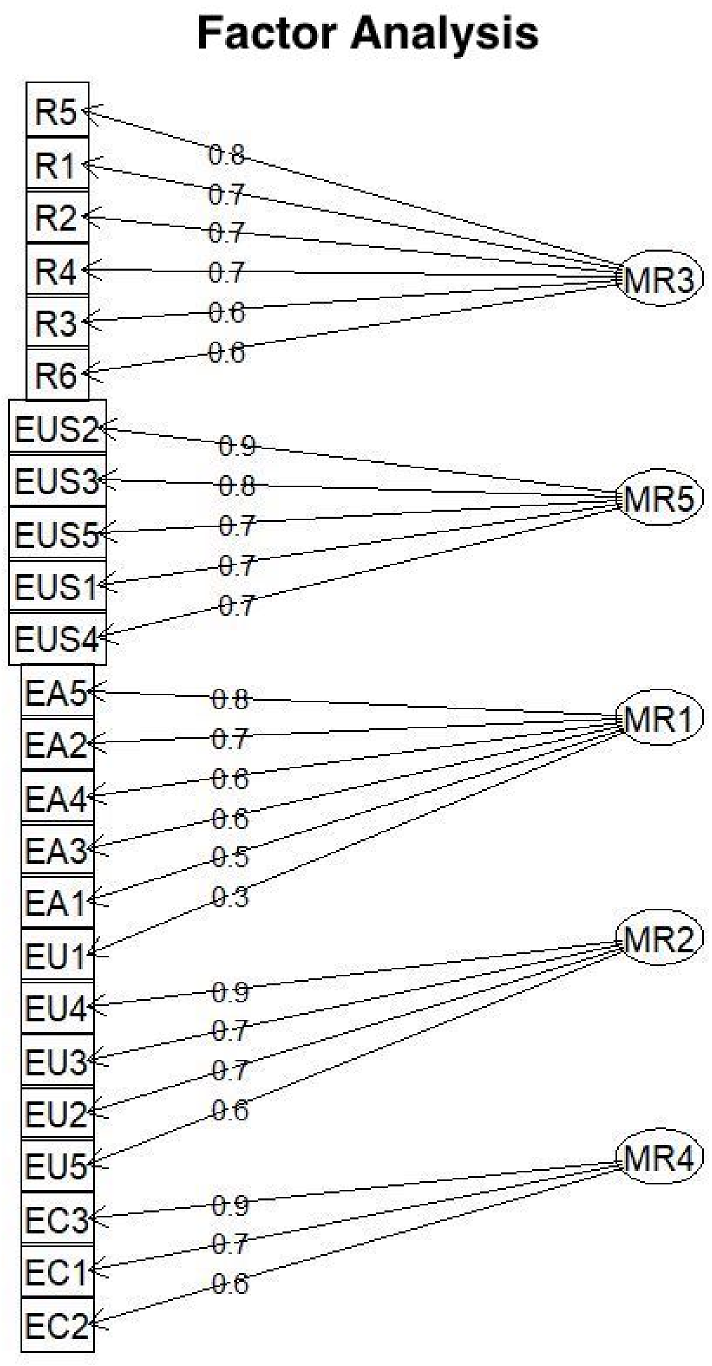


Fig. 2.7: EFA results

In the diagram, some observed variables and latent variables are not linked because their factor loadings are very small and, so, are ignored by `R`. As seen in the diagram, as the loading factor of EU1 is $0.3 < 0.5$, it is excluded.

2.3.4 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was performed to confirm the variability of the variables in this study. The observed variables are: EA1, EA2, EA3, EA4, EA5, EU2, EU3, EU4, EU5, EUS1, EUS2, EUS3, EUS4, EUS5, EC1, EC2, EC3, R1, R2, R3, R4, R5, R6. The latent variables are defined to be: EA, EU, EUS, EC, R.

Using chi squared test, we get $\chi^2 = 493.187$, $df = 220$, $\chi^2/df = 2.242$ and p-value=$0.000 < 0.05$. The following table shows the values of various indices in CFA:

Table IV: Table of Fit Indices of CFA

Fit Index	Value	Accepted Region
GFI	0.902	> 0.9
AGFI	0.877	> 0.9
NFI	0.902	> 0.9
NNFI	0.934	> 0.9
CFI	0.943	> 0.9
RMSEA	0.058	< 0.08
SRMR	0.053	< 0.08
TLI	0.934	> 0.9
PNFI	0.784	> 0.5
PGFI	0.719	> 0.5

Even though the value of AGFI is not above 0.9, it is sufficiently close and is supported by the other fit indices, so we do accept it as satisfactory.

From the values of fit indices above and chi-squared test, we see that the model is consistent with the data. These CFA results confirmed satisfactory discriminatory value and showed no bias of the common method bias. The three important indicators of convergent validity are factor loadings (standardized estimates), the average variance extracted (AVE) and composite reliability (CR). The standardized estimates of each construct ranged from 0.650 to 0.957 and were statistically significant (p-values). AVE ranged from 0.546 to 0.692 and CR ranged from 0.829 to 0.893. The results of standardized estimates, AVE and CR were all in the acceptable region, thereby providing support for convergent validities of constructs [6].

Table V: Standardized regression weights of items

Construct	Item	Standardized Estimates	CR	AVE	p-value
EA	EA1	0.683	0.872	0.578	0.000
	EA2	0.835			
	EA3	0.726			
	EA4	0.694			
	EA5	0.848			
EU	EU2	0.693	0.829	0.554	0.000
	EU3	0.690			
	EU4	0.924			
	EU5	0.638			
EUS	EUS1	0.650	0.893	0.631	0.000
	EUS2	0.946			
	EUS3	0.907			
	EUS4	0.713			
	EUS5	0.712			
EC	EC1	0.780	0.869	0.692	0.000
	EC2	0.744			
	EC3	0.957			
R	R1	0.786	0.878	0.546	0.000
	R2	0.729			
	R3	0.695			
	R4	0.713			
	R5	0.811			
	R6	0.689			

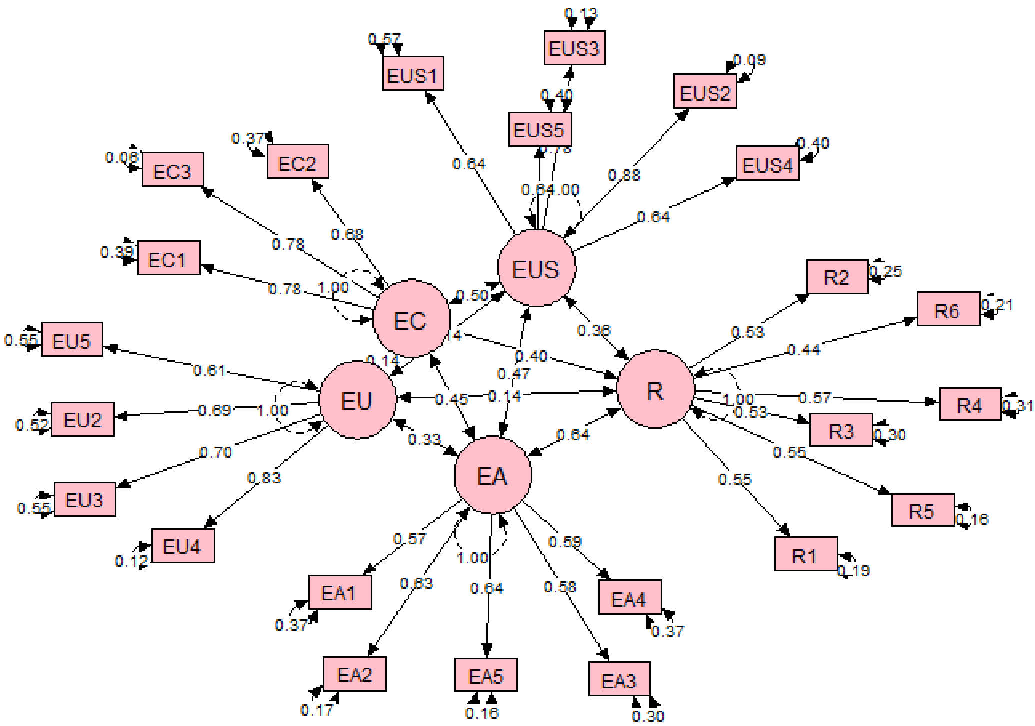


Fig. 2.8: CFA results

2.3.5 Structural Equation Modeling

Structural Equation Modeling (SEM) was used to analyse structural relationships. The underlying variable is defined to be EI.

Using the chi-squared test, we get $\chi^2 = 529.021$, $df = 225$, $\chi^2/df = 2.351$ and p-value=0.000 < 0.05. The following table shows the values of various indices in SEM:

Table VI: Table of Fit Indices of SEM

Fit Index	Value	Accepted Region
GFI	0.893	> 0.9
AGFI	0.869	> 0.9
NFI	0.895	> 0.9
NNFI	0.928	> 0.9
CFI	0.936	> 0.9
RMSEA	0.060	< 0.08
SRMR	0.062	< 0.08
TLI	0.928	> 0.9
PNFI	0.796	> 0.5
PGFI	0.728	> 0.5

In some topics, due to the limitation of sample size, it is difficult for the GFI and NFI value to reach 0.9 because this index depends a lot on the number of scales, the number of observed variables and the sample size. Therefore, if the GFI value is below 0.9 but from 0.8 or higher, it is still accepted according to studies by Baumgartner and Homburg [9] and Doll et al. [10].

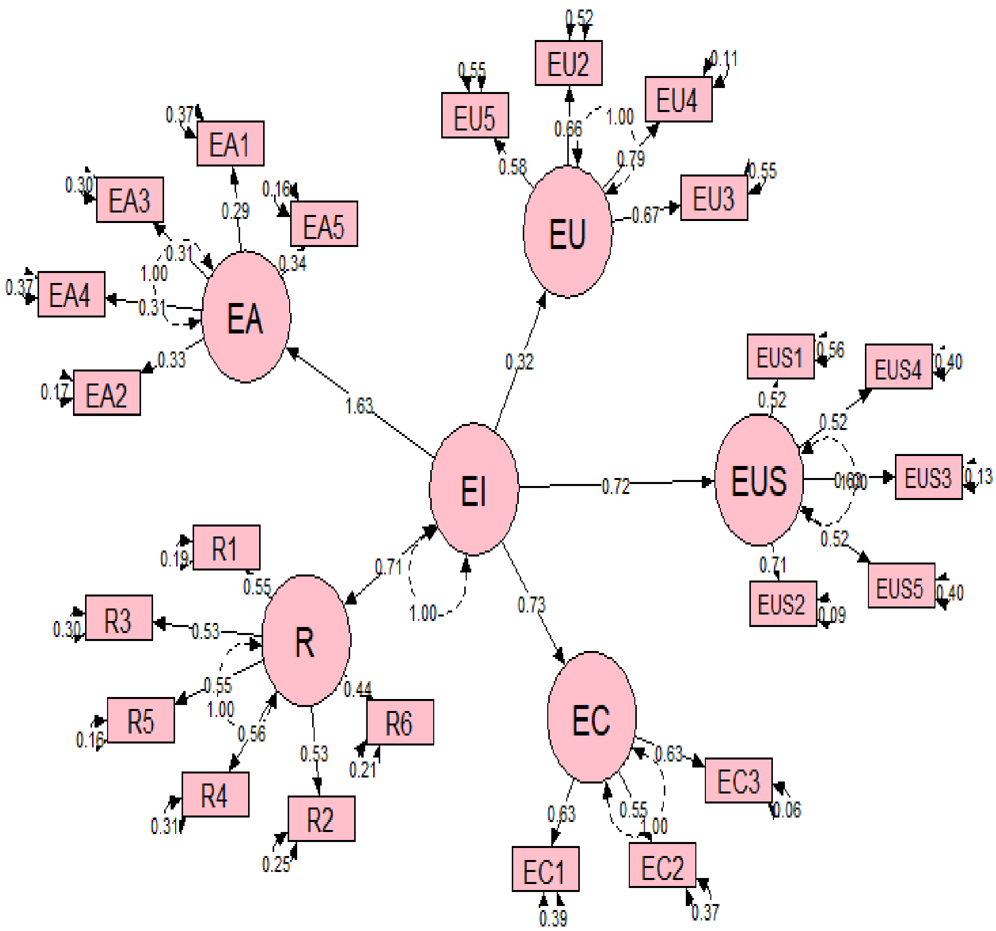


Fig. 2.9: SEM results

2.3.6 Regression Analysis

This study adopted Regression Analysis to investigate the relationship among the variables Emotion Intelligence (EI) and Teamwork Results (R). From the Regression Analysis, we see that Emotion Intelligence has a positive impact on Teamwork Results. (Slope=0.5674>0, p-value=0.000<0.05). Hence, our Hypothesis is true.

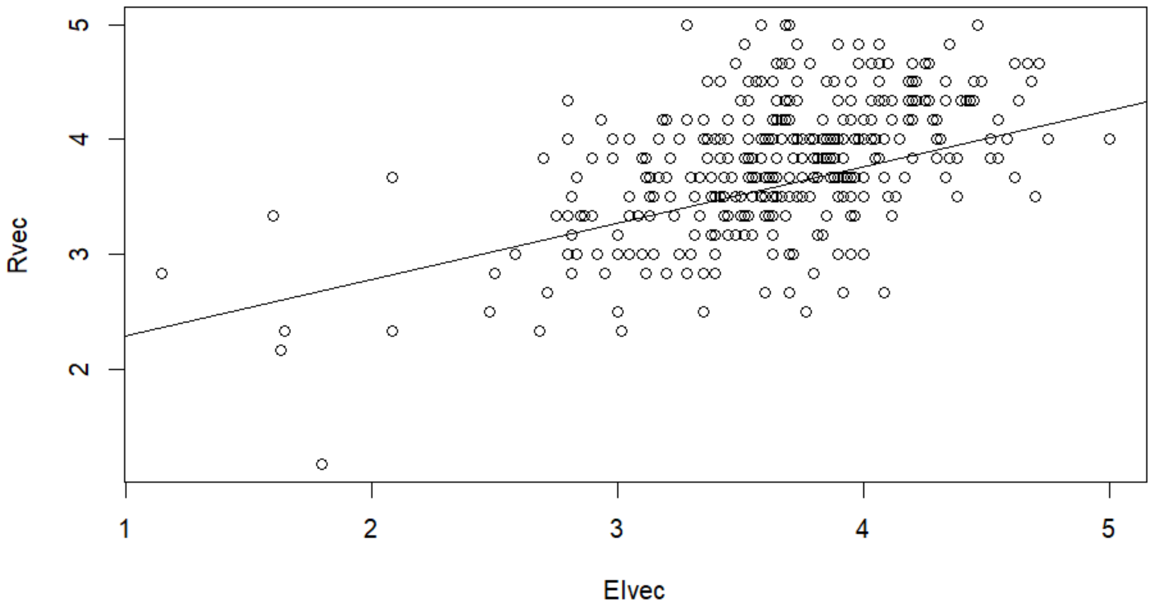


Fig. 2.10: Linear Regression of EI and R

Chapter 3

Our Extension

3.1 Method of Data Collection

To collect the data, we made a Google Form Questionnaire and sent it to university student groups. We kept the form open for three weeks and collected data of 122 students.

3.2 Data Analysis

The characteristics of the sample has been described in the table below:

Table VII : Characteristics of Sample

Demographic Information	Frequency	Number of Respondents	Percentage (%)
Gender	Female	48	39.3
	Male	74	60.7
Year of Students	1st	68	55.7
	2nd	25	20.5
	3rd	14	11.5
	4th	3	2.5
	Other	12	9.8
Frequency of Group Working	Never	6	4.9
	Rarely	19	15.6
	Sometimes	57	46.7
	Usually	40	32.8

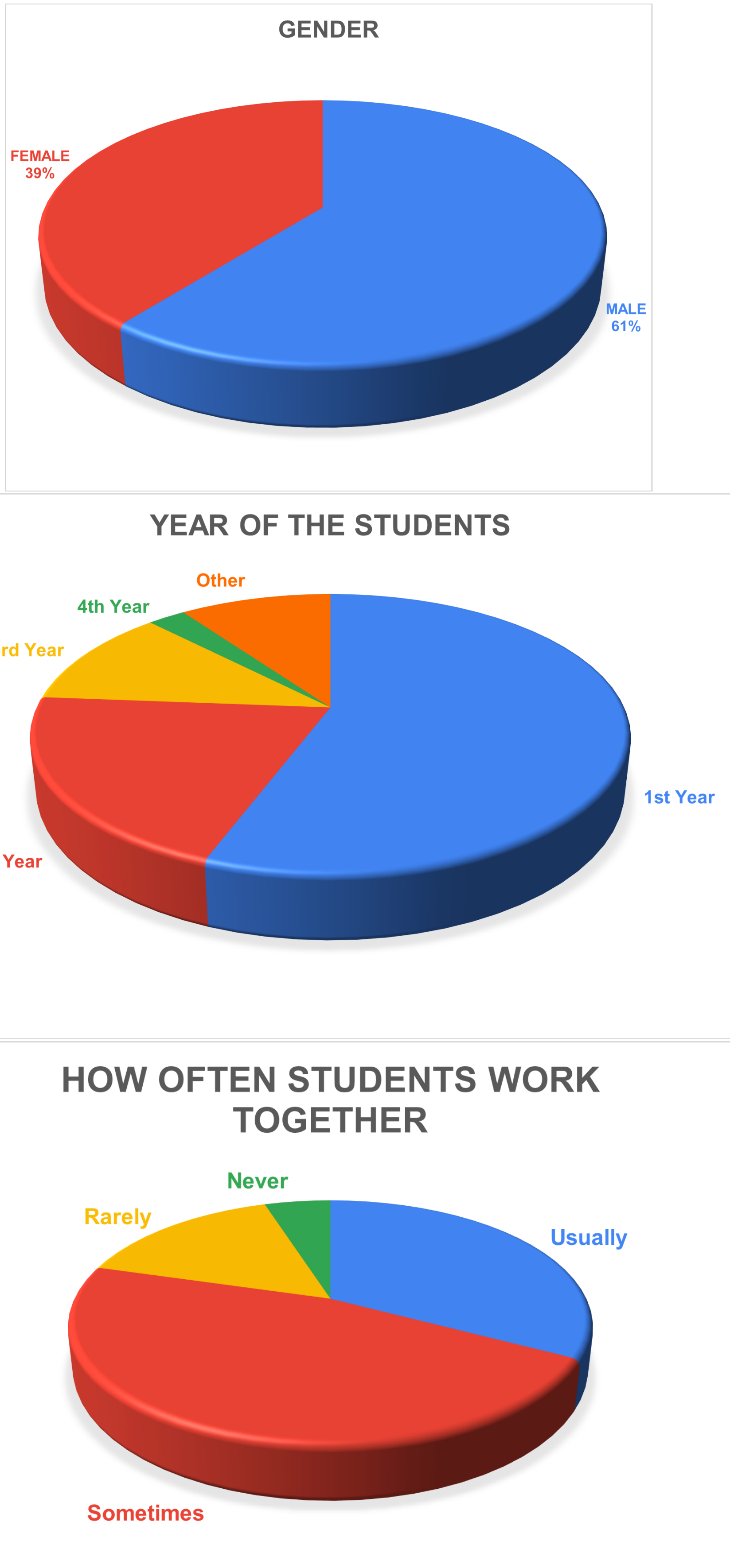


Fig 3.1: Profile of the Respondents

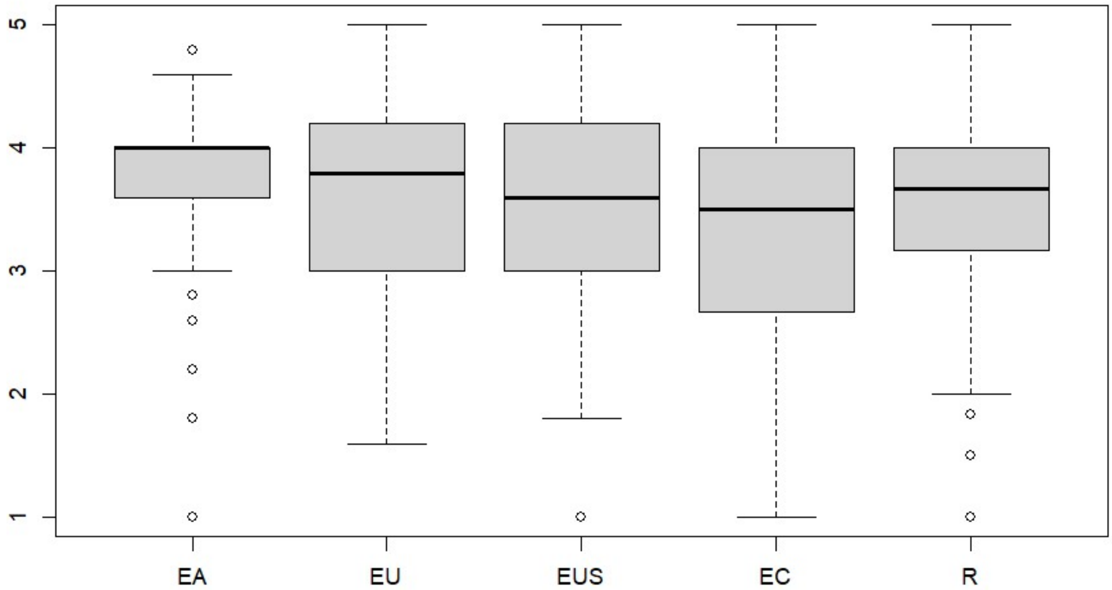


Fig. 3.2 Box plot of the Scales

Table VIII: Characteristics of Variables

Variables	Mean	SD	Skewness	Excess Kurtosis
Emotional Awareness (EA)	**3.793**	**0.622**	**-2.142**	**6.651**
EA1	3.721	0.816	-1.468	3.184
EA2	3.926	0.740	-1.355	3.578
EA3	3.828	0.850	-1.694	3.536
EA4	3.680	0.964	-0.935	0.559
EA5	3.811	0.806	-1.262	2.559
Emotional Usage (EU)	**3.595**	**0.813**	**-0.509**	**0.548**
EU1	3.869	0.833	-1.390	2.660
EU2	3.631	1.228	-0.588	-0.585
EU3	3.607	1.223	-0.602	-0.501
EU4	3.426	1.317	-0.428	-0.983
EU5	3.442	1.172	-0.481	0.404
Emotional Understanding (EUS)	**3.497**	**0.872**	**-0.585**	**-0.202**
EUS1	3.516	1.380	-0.621	-0.868
EUS2	3.434	1.143	-0.239	-0.887
EUS3	3.156	1.213	-0.077	-0.886
EUS4	3.705	1.140	-0.848	0.143
EUS5	3.672	1.102	-0.442	-0.453
Emotional Control (EC)	**3.402**	**0.922**	**-0.317**	**-0.593**
EC1	3.393	1.196	-0.474	-0.646
EC2	3.516	1.130	-0.386	-0.741
EC3	3.295	1.176	-0.313	-0.675
Teamwork Result (R)	**3.643**	**0.793**	**-0.661**	**0.963**
R1	3.754	1.070	-0.879	0.298
R2	3.459	1.046	-0.435	-0.411
R3	3.590	1.043	-0.483	-0.348
R4	3.795	0.899	-0.613	0.337
R5	3.607	1.033	-0.604	-0.051
R6	3.656	1.058	-0.539	-0.332

3.2.1 Cronbach's Test

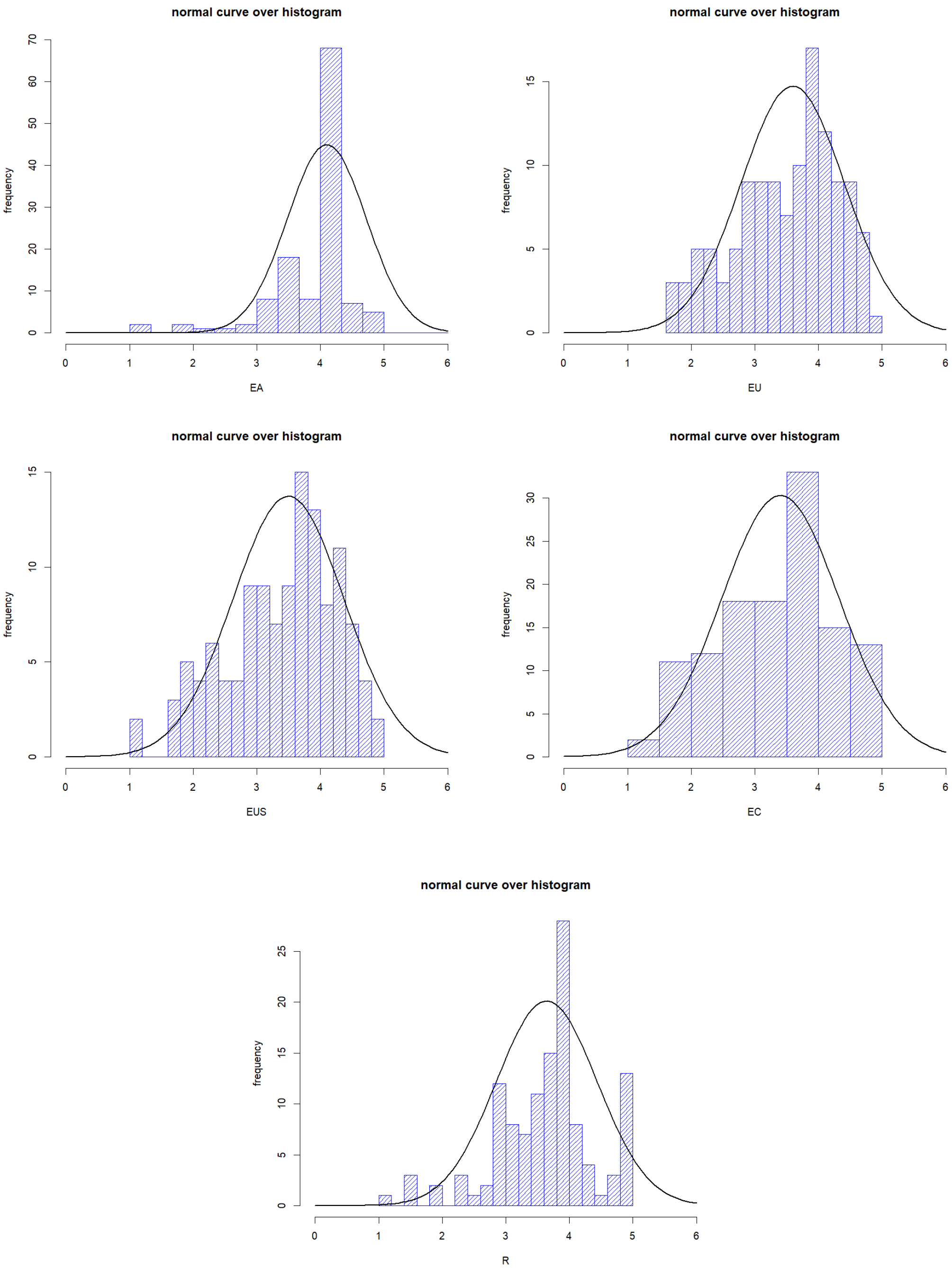


Fig. 3.3: Histograms with Normal Density Plot

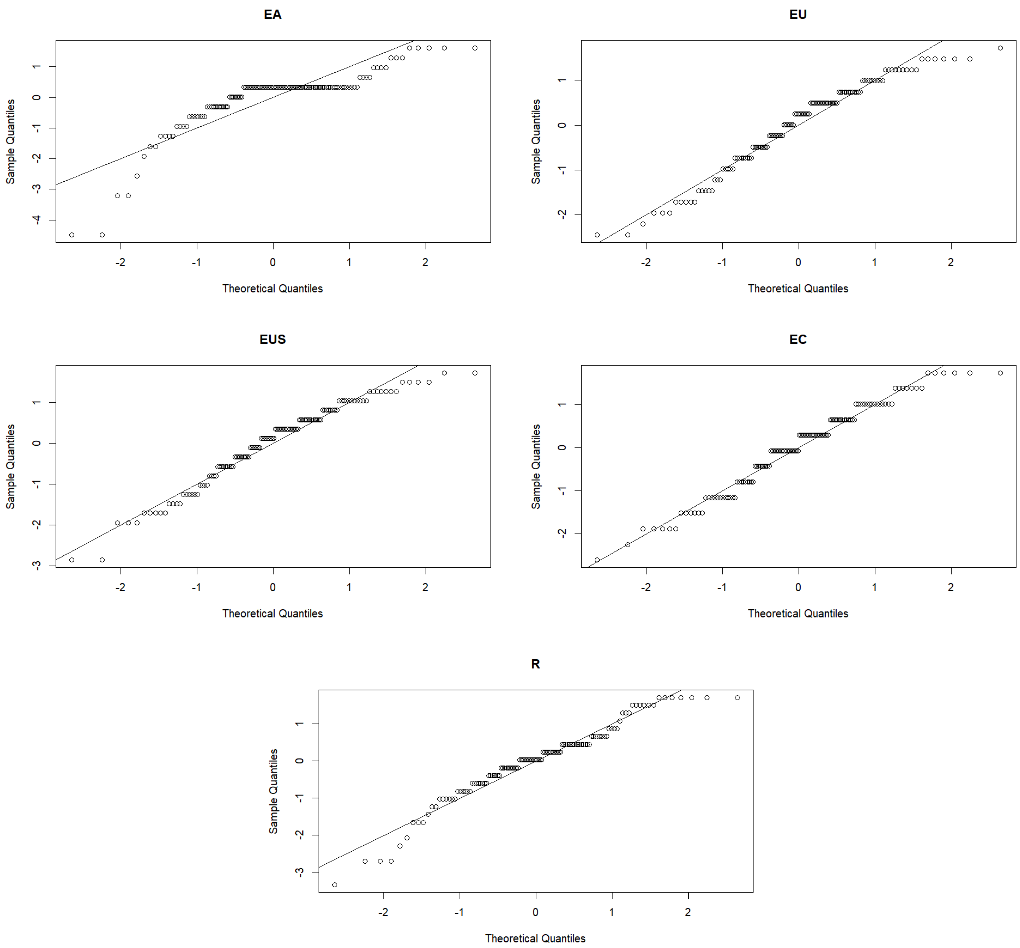


Fig. 3.4: Q-Q plot Comparison

From the comparisons above, it can be seen that the data is normally distributed. Hence, Cronbach's Alpha Reliability Test can be performed on the data.

Table IX: Cronbach's Alpha Values

Item	Cronbach's α
EA	0.795
EU	0.735
EUS	0.777
EC	0.698
R	0.865

As all values of α are near or greater than 0.7, the data has an acceptable level of reliability. We conclude that the data is appropriate for Factor Analysis.

3.2.2 Correlation Matrix

The heat map correlation matrix of the data is given below:

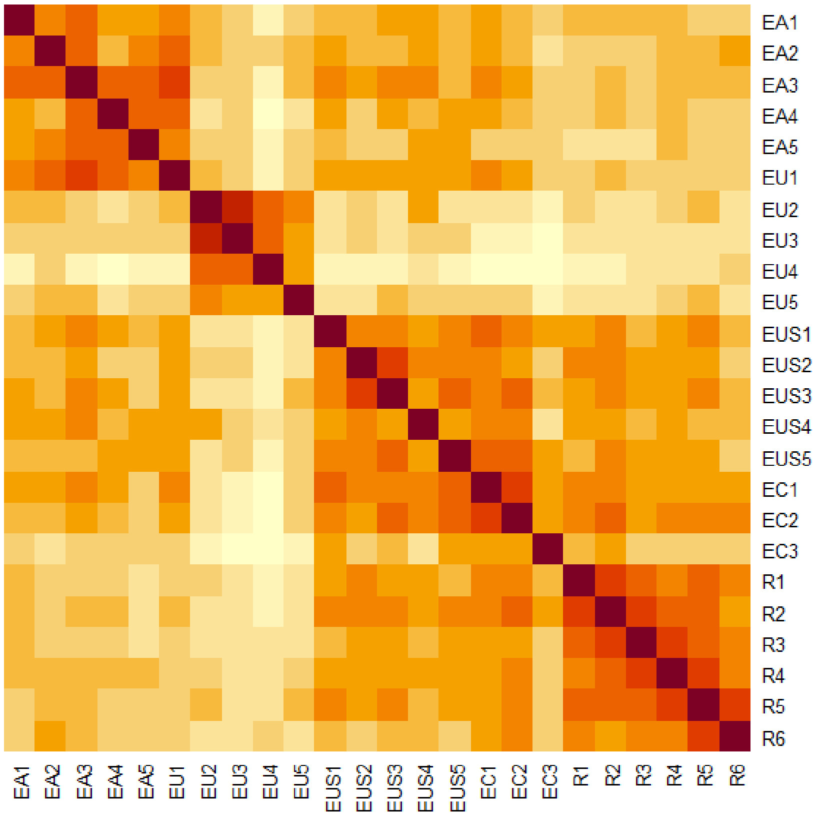


Fig. 3.5: Heat Map of Correlation Matrix

3.2.3 Exploratory Factor Analysis

Now we proceed doing Exploratory Factor Analysis (EFA) on the data. Doing the Bartlett's test, we get that p-value=0.000 $<$ 0.05, so we can conclude from Bartlett's test that the variables are indeed correlated.

Next, we perform the KMO (Kaiser-Meyer-Olkin) test which gives $KMO = 0.79 > 0.5$.

Hence, we can proceed with Exploratory Factor Analysis.

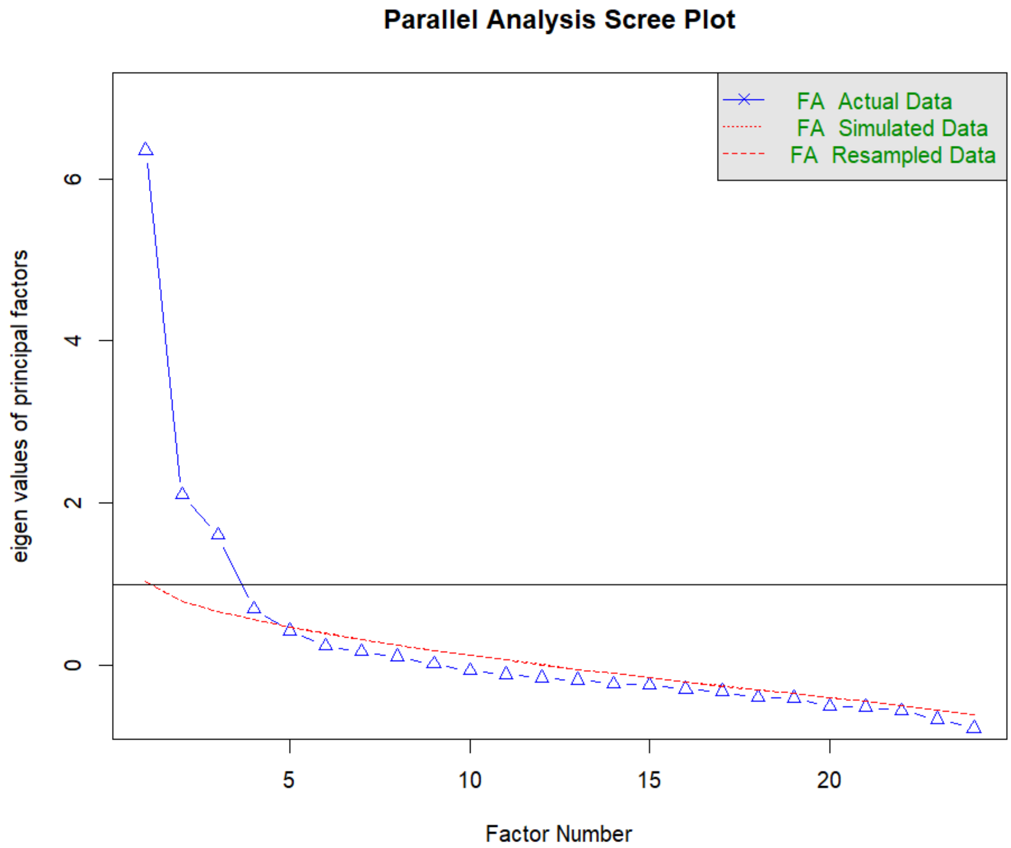


Fig. 3.6: Scree Plot

From the Parallel Analysis, we can see that we need to retain 4 factors.

Next, we proceed with Exploratory Factor Analysis with number of factors = 4.

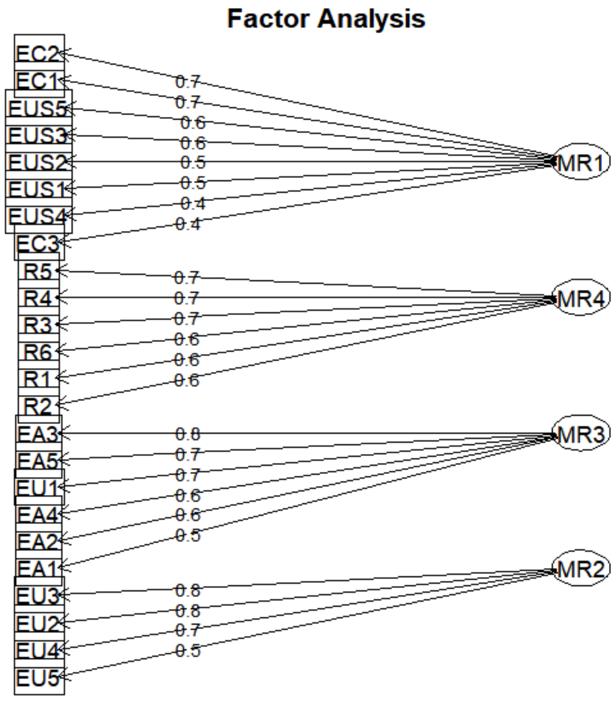


Fig. 3.7: EFA results

In the diagram, some observed variables and latent variables are not linked because their factor loadings are very small and, so, are ignored by `R`. As seen in the diagram above, we need to reject EUS4 and EC3 as their loading factor = $0.4 < 0.5$.

We get that the cumulative variance = 50% $\geq$50%, so we can perform Confirmatory Factor Analysis.

3.2.4 Confirmatory Factor Analysis

Now, Confirmatory Factor Analysis is done on our data. The observed variables are: EA1, EA2, EA3, EA4, EA5, EU1, EU2, EU3, EU4, EU5, EUS2, EUS3, EUS1, EUS5, EC1, EC2, R1, R2, R3, R4, R5, R6. The latent variables are taken to be: X1, X2, X3, X4.

Using chi-squared test, we get that $\chi^2 = 379.709$, $df = 207$, $\chi^2/df = 1.834$ and p-value=$0.000 < 0.05$. The following table shows the values of various indices in CFA:

Table X: Table of Fit Indices of CFA

Fit Index	Value	Accepted Region
GFI	0.792	> 0.9
AGFI	0.741	> 0.9
NFI	0.735	> 0.9
NNFI	0.832	> 0.9
CFI	0.853	> 0.9
RMSEA	0.084	< 0.08
SRMR	0.076	< 0.08
TLI	0.832	> 0.9
PNFI	0.646	> 0.5
PGFI	0.635	> 0.5

From the table above, it can be seen that the fit indices GFI, AGFI, NFI, NNFI, CFI, RMSEA, TLI say that our model is not a good model for the data. One of the reasons for this can be the limitation in the sample size. The three important indicators of convergent validity are factor loadings (standardized estimates), the average variance extracted (AVE) and composite reliability (CR). The standardized estimates of each construct ranged from 0.580 to 0.868 and were statistically significant (p-values). AVE ranged from 0.469 to 0.523 and CR ranged from 0.800 to 0.867.

Table XI: Standardized regression weights of items

Construct	Item	Standardized Estimates	CR	AVE	p-value
X1	EA1	0.601	0.839	0.469	0.000
	EA2	0.643			
	EA3	0.829			
	EA4	0.621			
	EA5	0.626			
	EU1	0.759			
X2	EU2	0.823	0.800	0.514	0.000
	EU3	0.868			
	EU4	0.650			
	EU5	0.451			
X3	EUS1	0.648	0.844	0.476	0.000
	EUS2	0.582			
	EUS3	0.683			
	EUS5	0.676			
	EC1	0.773			
	EC2	0.761			
X4	R1	0.717	0.867	0.523	0.000
	R2	0.780			
	R3	0.756			
	R4	0.743			
	R5	0.745			
	R6	0.580			

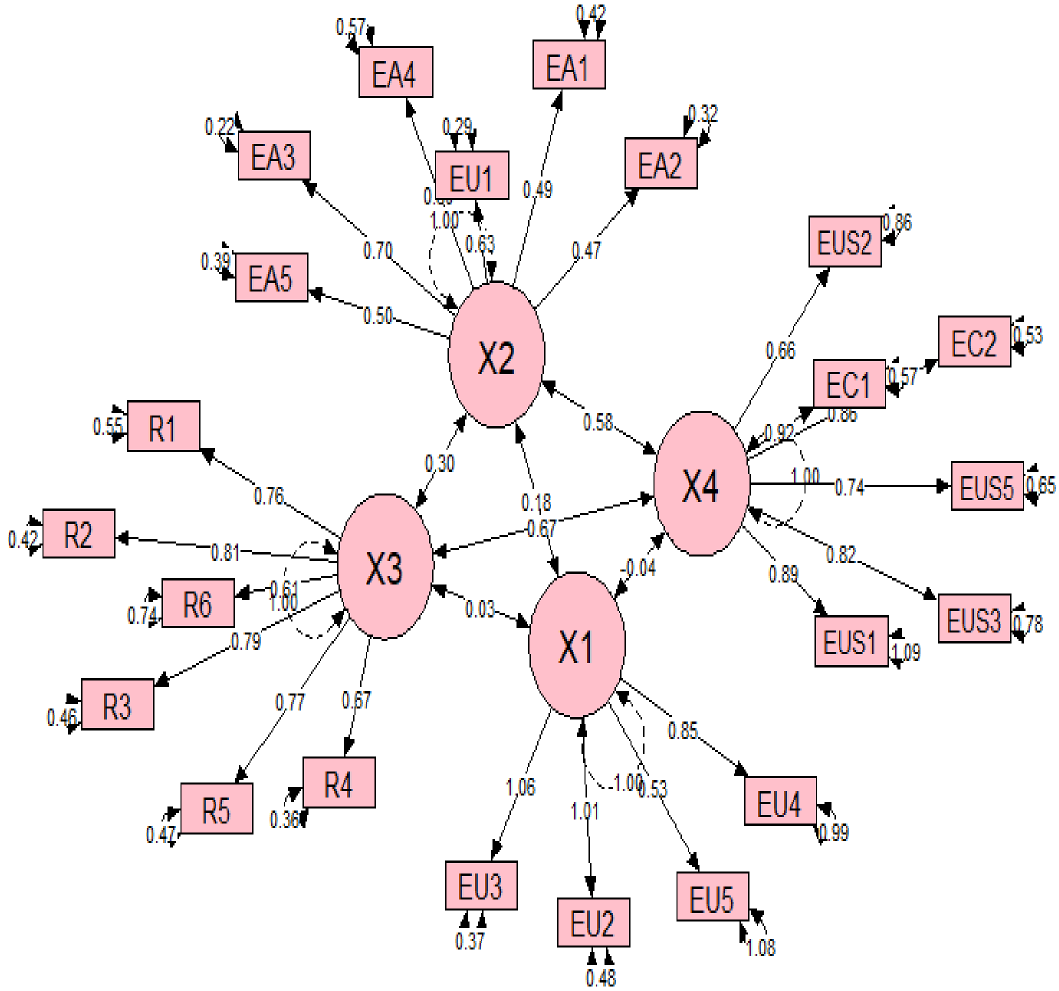


Fig. 3.8: CFA results

3.2.5 Reasons of Failure

1. **Small Sample Size:** The sample might be too small to carry out Factor Analysis.
2. **Central Tendency Bias:** Some participants might have avoided using 1 and 5 out of a desire to avoid being perceived as having extremist views.
3. **"Faking Good":** The participants might have provided answers that they believe society will consider more favourable than their true beliefs. (this might explain the unnatural number of 4's in EA).

Chapter 4

Conclusion

4.1 Original Paper

The purpose of the study was to understand the relationship between emotional intelligence and students' group work results. The research hypothesis is accepted with $p < 0.01$

Emotional Intelligence is positively related to student group work's result, this conclusion is acknowledged in Tucker et al. [17], Grossman [18], Luke et al. [24], Muhammad [25]. Gujral and Ahuja [8] affirmed that Emotional Intelligence plays an important role in the way team members cooperate and collaborate on the same task. Therefore, for the group to work smoothly and achieve high results, it is necessary to have an impact on the Emotional Intelligence of each member in the group.

4.2 Our Extension

As was demonstrated, our model did not produce sufficiently acceptable fit indices for the data collected from Indian universities, so we cannot draw a proper conclusion by performing analysis on this data.

It is possible that the problem might be explained by some issue with the method of data collection, if not the lacking number of observations (122) as compared to the amount collected by the original authors (372).

Appendix A

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