American University of Sharjah

Sharjah, United Arab Emirates

STA 401 - Introduction to Data Mining

Assessing Student Satisfaction with the 4-Day Work Week Shift: AUS Case Study

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ABSTRACT

The four-day work week is an initiative being considered and implemented by governments and companies that hopes to improve productivity and overall well-being of people. This project investigates the impact of a four-day work week on student satisfaction, focusing on factors such as work-life balance, quality of learning, academic performance, engagement in physical activity and psychological distress. The study analyzed data obtained from a survey conducted among a sample of students at the American University of Sharjah. Principal Component Analysis and Exploratory Factor Analysis are employed to identify the key dimensions of student satisfaction. These factors are subsequently confirmed and refined using CFA, ensuring the reliability and validity of the measurement model. With the established factors, an Ordinal Logistic Regression model is applied to assess the effect of the latent factors on student satisfaction. The findings indicate that psychological distress, quality of learning and work-life balance have the greatest effect on students' satisfaction with the four day workweek shift. The study concludes that the 4-day work week is successful in ensuring that students suffer less stress, spend more time with their families and enjoy a higher quality of learning.

I.INTRODUCTION

Throughout the years, several countries have been searching for methods on improving the wellbeing and happiness of their citizens as a fundamental aspect of governance. Countries such as Finland, Bhutan, Denmark, New Zealand and the United Arab Emirates (UAE) rank high in global happiness reports [1]. These countries have actively pursued initiatives to enhance the quality of life of their citizens, by placing a strong emphasis on mental health, physical health, and work-life balance. Among the topics frequently discussed by many of these countries is the concept of implementing a four-day workweek, offering students and employees the benefit of an extended weekend. The concept revolves around the idea of reducing the usual five-day workweek to four days, hence providing individuals the opportunity to spend time pursuing personal goals and activities.

The global implementation of a four-day workweek has gained significant attention in recent years, where companies and governments were interested in exploring the potential benefits for their employees in particular. In most cases, the four day workweek shift does not equate to a reduced number of hours, rather, the daily working hours are extended to compensate for the fifth day. Although such a drastic change in the work environment cannot happen overnight, a total of 18 countries were reported to have implemented this system. These countries include, but are not limited to: Australia, Canada, Ireland, Scotland, UK, and the UAE [2].

During 2022, the government of Sharjah announced the adoption of a four-day working week and three-day weekend. As per a statement from the government, this decision was made to maintain pace with global development and improve its competitive position across a variety of industries while supporting the business environment and the economic market [3]. The new system impacts public sector employees including government staff and academic institutions. With increasing interest in work-life balance and employee well-being, many academic institutions across the country are considering implementing a four-day working week as a means of improving productivity and satisfaction. However, there is limited empirical evidence on the effectiveness of such a policy.

The problem is to develop a model that can accurately assess whether the four-day working week is satisfactory or not, based on factors such as student productivity, educational satisfaction, and academic performance. To address this problem, data needs to be collected and analyzed to identify the impact of a four-day working week on the various aspects mentioned above. This will enable institutions to make informed decisions about whether to implement a four-day working week and how to optimize its implementation to maximize productivity and student well-being. The case study chosen for this research is the American University of Sharjah, but it can be extrapolated to other institutions across Sharjah.

II. LITERATURE REVIEW

A study [4] has been conducted in the UK where 61 companies and approximately 2900 workers signed up to trial a reduced work-week over the span of six months. The purpose of this study was to assess whether reducing the number of working hours would benefit companies through employee satisfaction and therefore better work performance and productivity. The study did not in fact restrict the companies to strictly follow a 4-day work week instead of a 5-day work week, rather it was sufficient enough to simply reduce the number of working hours for their employees, in whichever way they thought would be best for their company. The outcomes of this study happened to be in favor of the reduced working hours, in which companies rated the experience of this trial an overall 8.5/10. 91% of organizations highlighted that they are definitely continuing or planning to continue a 4-day work week, whereas 4% are leaning towards continuing and only 4% are definitely not going to continue. Additionally, the revenue of certain companies increased by 35% over the six-months trial period when compared to a similar period of time from previous years. As per the employees, the study reported an increase in life and job satisfaction, physical and mental health, as well as the time each employee spent exercising. The study also reported a reduction in employee burnout, stress and fatigue. All of which are important factors to consider when assessing the success of such a drastic change. Although this study is extremely important for interpreting the success of the 4 day workweek pilot, it was not published as a research project since the survey questions were not obtained through literature.

According to available literature, the United States was among the first countries to implement a pilot program for a four-day workweek. Specifically, in 2008, the state government of Utah launched a three-year-long pilot initiative [5]. The initiative was introduced to address budget constraints and limited resources, making it a strategic response to the prevailing economic and resource challenges. Thousands of employees were included in the pilot, which sought to assess the impact of compressed workweeks on productivity and operational effectiveness [6]. The pilot program, which was initially implemented in 2008, came to an end in 2011 primarily because a legislative audit conducted in 2010 revealed that the anticipated savings did not materialize as expected [6]. One contributing factor to this outcome was the decline in energy prices during the pilot period [6].

A meta-analysis [7] of the implementation of the 4-day work week in schools in the United States was done to assess the impact of it on financial, student achievement, and other student outcome factors. Changing to a shorter workweek reduced the costs associated with transportation, food, energy, and substitute teacher pay. Additionally, student achievement was found to either improve or remain unchanged with the switch, while factors such as school dropout rate, attendance, and participation in extracurriculars improved. Overall, changing to a shorter workweek was associated with an improvement in all areas of interest and was received positively by students, teachers, and parents alike.

Similarly, a study [8] was conducted in the United Arab Emirates addressing the implementation of the four day workweek and three day weekend in schools. The study was conducted on Sharjah schools by the Sharjah Private Education Authority (SPEA) in order to evaluate the reduced workweek system and assess the impact it had on students. This study was conducted with the assistance of 31,198 families of students of 70 different nationalities, 7,000 teachers and 127 schools [8]. The study showed an overall improvement in the students' performance, with a 77% increase in their academic achievements as well as a 78% increase in their social skills and interactions with one another. Additionally, the research study showed a 74% increase in the students' problem solving skills, a 73% increase in their time management abilities, as well as an 88% increase in the quality time that was spent with their families [8].

One study of relative importance was conducted at the University of Michigan Medical School, in which a limit on the maximum number of clinical duty hours was imposed [9]. The motivation behind this study stems from another study that reported a strong correlation between extended numbers of working hours and the development of moderate (and sometimes severe) depression [10]. The Michigan University study compared two student groups in order to assess the impact of reducing the number of clinical working hours. The first student group completed their clinical hours prior to the implementation of the work-hour restrictions, while the second group completed their work hours the same year the restrictions were imposed. The results happened to be in favor of the students' mental health, in which they experienced less fatigue, an increase in the number of sleep hours and a reduction in attention failures. However, the authors reported a reduction in the resident experiences in surgery fields, quality of patient care which was correlated with a reduction in the continuity of patient care, and little evidence regarding the improvement of patient care.

Despite the topic's increasing prominence, scholarly studies focusing on the implementation of a four-day workweek within the context of higher education institutions remain scarce. Although [9] was conducted at a university level, it did not really assess the implementation of the four day workweek, rather it just assessed the impact of reducing the number of working hours on medical students. It is important to note that the four day workweek pilot does not aim to reduce the total number of hours within an organization, instead it intends to maintain the total number of hours by spreading them over four days instead of the usual five. It is advantageous in the sense that it allows individuals to have prolonged weekends during which they can recharge without compromising their work productivity and efficiency.

III. METHODOLOGY

a) Data Collection and Participants

This project focused on the acquisition of data pertaining to diverse facets of a student's life within an academic institution, encompassing their psychological distress, physical health, academic performance, work-life balance, quality of learning, and overall satisfaction. Given that this data was to be sourced directly from students themselves, an online survey was selected as the preferred method of data collection. Online surveys were deemed optimal due to their user-friendly nature and cost-effectiveness. Moreover, they facilitated efficient data gathering from a sizable sample, allowing respondents to complete the survey at their convenience and pace.

The survey questions employed in this study were formulated by drawing upon existing literature and standardized surveys that have been widely used to assess specific factors of interest. The selection of these surveys was based on their established reliability and validity in measuring key constructs such as psychological distress, work-life balance, and quality of learning.

To measure psychological distress, we employed the Perceived Stress Scale (PSS), which has been extensively utilized in previous research [11]. The PSS assesses individuals' perceptions of stress levels and their ability to cope with stressors.Work-life balance was assessed using the Work and Family Conflict Scale (WAFCS), a well-established instrument used to evaluate the degree of conflict and balance between work and personal/family life [12]. This scale captures various aspects of work-life integration and identifies potential sources of conflict or harmony between work and personal responsibilities. To evaluate the quality of learning experiences, we utilized a student experience questionnaire developed at Carleton University in Canada [13]. This questionnaire is specifically designed to capture students' perceptions of the learning environment, teaching methodologies, and overall educational experiences.

The detailed survey outline and the specific questions used in the study can be found in the appendix section of this report. These questions were carefully selected and adapted to suit the research objectives and context of the study, ensuring the alignment with the constructs and concepts of interest.

By employing established and validated survey instruments, we aimed to collect reliable and comparable data on psychological distress, work-life balance, and quality of learning. This approach allowed us to leverage the existing body of research and ensure the robustness and validity of our findings in these areas.

The statistical population of interest for this study consisted of students enrolled at the American University of Sharjah (AUS). AUS boasts a student body exceeding 5000 individuals representing 91 different nationalities, thereby constituting an adequate population size. However, for the purposes of sample collection, only students who enrolled starting from the Fall 2021 semester were considered eligible. This criterion ensured that participants possessed the ability to accurately compare and contrast their university experience under both a five-day and four-day working week. Consequently, the sample pool excluded current freshmen students, with a primary focus on upperclassmen. Additionally, undergraduate alumni who were presently enrolled in master's programs at AUS were targeted to glean insights into their experiences with both the five-day and four-day working week structures.

In total, 66 survey responses were recorded, encompassing various majors across three distinct colleges at AUS. Among these 66 responses, six were deemed trial responses and were consequently excluded from the data analysis portion of the project. Ultimately, the distributions based on different factors can be succinctly summarized through the utilization of bar plots.

b) Data Cleaning and Preprocessing

The initial step in the data cleaning process involved the exclusion of the first six rows from the exported Google Sheets CSV file. These rows were designated as trial responses, intended solely for assessing the relevance of the survey questions. Furthermore, certain columns containing unstructured data and lacking significant information were eliminated from the dataset. These columns included the timestamp, email address, major, and commute distance.

Subsequently, specific survey questions that had been present during the trial phase but were ultimately excluded from the final survey distribution were also removed from the dataset. This action was taken due to the substantial absence of responses for the majority of rows, rendering these questions inconsequential for subsequent analyses.

Following the elimination of null values and irrelevant columns, the data underwent conversion into two distinct formats to facilitate different types of analyses. Initially, the data was transformed into ordinal factors, facilitating the generation of visualizations and exploratory data analysis. Subsequently, the survey factors were converted into integer values, enabling principal component analysis (PCA) and factor analysis.

To enhance readability and streamline subsequent plotting and algorithmic processes, all columns were renamed using concise and intelligible symbols. This simplified referencing and enhanced overall clarity throughout the data analysis pipeline.

c) Exploratory Data Analysis

Upon successful loading of the data, we proceeded to conduct the Chi-Square test to examine the relationship between each predictor variable within the dataset and the response variable, specifically, the variable representing Satisfaction. The Chi-Square test outcomes served to detect any statistically significant associations between the predictors and the response. This information proved instrumental in enhancing our understanding of the results obtained from subsequent dimensionality reduction techniques employed.

Following the completion of the Chi-Square test, we generated a correlation matrix to visualize the interrelationships among all variables in the dataset. The resulting plot revealed notable patterns wherein variables belonging to the same metric (e.g., work-life balance) exhibited substantial positive or negative correlations with one another. These findings suggested that employing dimensionality reduction techniques, such as Principal Component Analysis (PCA) or Factor Analysis, would be advantageous for consolidating these closely related factors into composite variables.

d) Dimensionality Reduction Techniques

The first dimensionality reduction method applied to the dataset was Principal Component Analysis (PCA). PCA is a multivariate statistical technique used to transform a set of correlated variables into a new set of uncorrelated variables, called principal components. The aim of PCA is to capture the maximum amount of variation present in the original dataset by projecting the data onto a lower-dimensional space while retaining as much information as possible. PCA allows for dimensionality reduction by selecting a subset of the principal components that capture a significant proportion of the total variance. By discarding the components with low variance, the dimensionality of the data is reduced while preserving the most important patterns and structures. Once PCA was conducted, we observed the resulting biplot and scree plot, to optimize the selection of the number of principal components.

The second dimensionality reduction method applied to the dataset was Factor Analysis (FA). Factor Analysis is a statistical technique used to identify underlying latent factors or constructs that explain the patterns of interrelationships among a set of observed variables. It aims to reduce the dimensionality of the data by extracting a smaller number of unobservable factors that capture the shared variance among the observed variables.

Factor analysis can be further classified into Exploratory Factor Analysis, and Confirmatory Factor Analysis. Exploratory Factor analysis allows for dimensionality reduction by specifying the reduced number of variables (latent factors) that capture the majority of the variance in the observed variables. EFA divides the original variables into the new latent factors based on their correlation. By identifying the latent factors, it becomes possible to explain the relationships between the observed variables in terms of a smaller number of underlying constructs. The reason EFA was conducted in this project although the factors were already classified into factors was primarily to assess the location of the physical activity variable. Since the physical activity section was composed of a single question, we wanted to see whether we should fit it with psychological distress, or with work-life balance. Similarly, the variables that compose the academic performance section were obtained from several different research studies, and so we wanted to see whether EFA would cluster them together or not.

Once EFA was conducted, Confirmatory Factor Analysis was then conducted. The latent factors were defined according to the survey outline, which includes psychological distress, academic performance, work-life balance, and quality of learning. The work-life balance section was split into two factors, 'WLB1N' capturing the first 5 questions WL1-WL5, and 'WLB2N' capturing the rest. Based on the CFA output, the model was adjusted by re-scaling some variables in addition to removing insignificant ones. By looking at the significant variables for each latent factor, new variables were then created by computing the median of the corresponding significant variables. These new variables were then used as inputs to an ordinal logistic regression model.

e) Testing Statistical Significance of Newly Generated Factors

After applying dimensionality reduction techniques, we conducted a rigorous evaluation of the generated principal components and factors by employing classification models. By applying these models to the transformed dataset, we aimed to assess the significance of these transformations in relation to the response variable. Specifically, we employed the Ordinal Logistic Regression model.

For Ordinal Logistic Regression, we performed the analysis on factors that were found to be significant according to our CFA. Additionally, we interpreted the regression coefficients to determine the magnitude of the effects and their statistical significance for each factor. Hypothesis testing, such as the Wald test or likelihood ratio test, was utilized to evaluate the statistical significance of the coefficients. These tests allowed us to ascertain whether the predictor variables had a meaningful impact on the outcome variable by determining if the coefficients significantly differed from zero. We applied a similar analysis to the obtained principal component values.

By employing the Logistic Regression model, along with the examination of regression coefficients and variable importance measures, we aimed to gain insights into the significant factors that influence the response variable. This analysis provided a comprehensive evaluation of the transformed dataset and allowed us to identify the most influential factors for further interpretation and decision-making.

IV. RESULTS AND FINDINGS

A. Exploratory Data Analysis

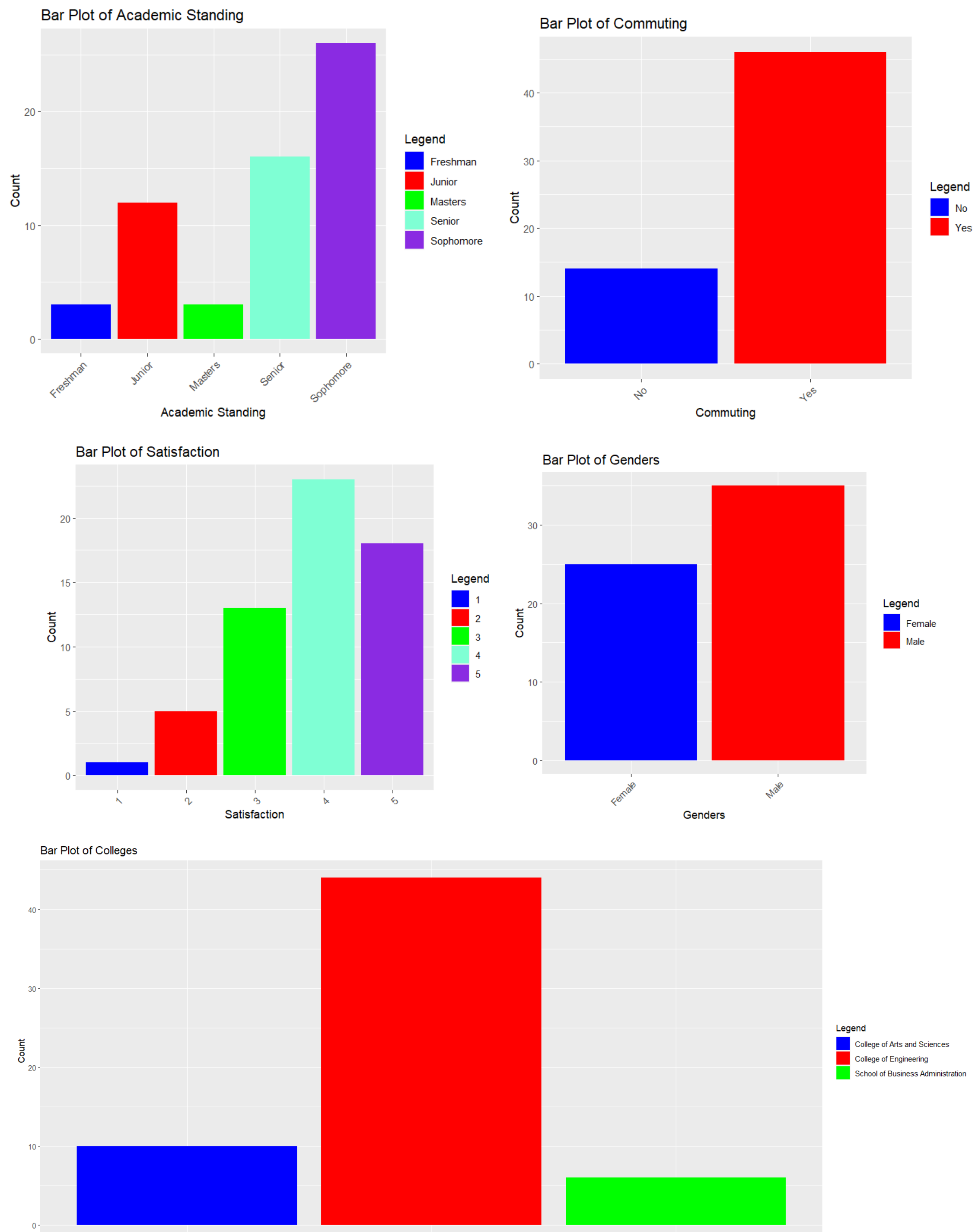


Fig 1: Bar plots highlighting the distribution of the survey respondents

Based on the analysis of the bar plots presented above, several conclusions can be drawn regarding the survey population under investigation:

- *Academic Standing*: The distribution of survey respondents across different academic standings reveals some notable patterns. It is evident that a significant proportion of the respondents were Sophomore students, followed by Senior students. In contrast, there were relatively fewer responses from Freshmen and Masters students. This distribution can be attributed to the lower enrollment of master's students at the American University of Sharjah (AUS) and the fact that Freshmen students have limited exposure to both the 4-day and 5-day working week, making it challenging for them to provide meaningful insights on the comparison between the two.
- *Commuting, Gender and College*: Observing the survey responses regarding commuting patterns, gender representation, and college affiliation, certain imbalances are apparent. A substantially larger proportion of students who commute to and from the university are represented among the survey respondents. Additionally, there is a noticeable disparity between male and female respondents, with a higher proportion of male participants. Furthermore, significant discrepancies are observed across the four colleges at AUS, with no responses recorded from students in the College of Art, Architecture, and Design (CAAD), while a considerable number of responses originate from the College of Engineering (CEN). These discrepancies can be attributed to the inherent nature of sampling, where chance fluctuations can lead to an unequal representation of specific demographics in the survey sample.
- *Satisfaction*: Turning attention to the response variable of satisfaction, it is noteworthy that a higher percentage of positive satisfaction is observed among the survey respondents. This preliminary observation raises interesting implications as it suggests a generally positive perception and satisfaction with the 4-day working week. However, further analysis and interpretation of the results are required to explore and substantiate this hypothesis.

Variable	**X-Squared**	**df**	**p-value**
Age	15.889	24	0.8921
Gender	4.083	4	0.3949
Academic_Standing	19.773	16	0.2306
College	2.9079	8	0.94
Workload_Intensity	21.852	12	0.03922

Commuting	9.2538	4	0.05506
PD1	24.626	16	0.07669
PD2	25.028	16	0.06933
PD3	14.322	16	0.5747
PD4	11.817	16	0.7565
PD5	33.262	16	0.006822
PD6	22.824	16	0.1185
PD7	16.397	16	0.4256
PD8	8.2022	12	0.7691
PD9	18.663	16	0.2865
PD10	21.848	16	0.1482
PHY	22.692	16	0.1222
AP1	42.208	16	0.0003674
AP2	14.542	16	0.5584
AP3	23.422	16	0.1029
AP4	32.301	16	0.009136
AP5	27.265	16	0.03
WLB1	20.185	16	0.212
WLB2	23.228	16	0.1078
WLB3	8.195	16	0.9428
WLB4	24.793	16	0.07355
WLB5	12.562	16	0.7045
WLB6	15.206	16	0.5096
WLB7	18.714	16	0.2838
WLB8	16.009	12	0.1908
WLB9	20.191	16	0.2117
QL1	25.803	16	0.05686
QL2	11.588	12	0.4793

QL3	15.913	12	0.1952
QL4	20.278	16	0.208
QL5	16.448	12	0.1716
QL6	10.071	16	0.8629
QL7	27.399	16	0.03726
QL8	13.721	12	0.3189
QL9	29.913	16	0.01846

Table 1: Chi-Square Test Results

Based on the results of the Chi-Square test presented above, the rows in the above table that are highlighted in green indicate statistically significant associations with the response variable. These significant findings provide valuable insights into the potential factors that might have a meaningful impact on our confirmatory factor analysis. However, it is important to note that the significance of these variables can only be confirmed through further rigorous testing and analysis.

The Chi-Square test results serve as a preliminary indication of variables that show promising relationships with the response variable. These variables can guide our subsequent confirmatory factor analysis, which will enable us to examine the underlying latent constructs and their relationships more comprehensively. By considering the statistically significant variables identified in the Chi-Square test, we can develop a refined model that focuses on these key factors of interest.

Nevertheless, it is crucial to emphasize that the significance observed in the Chi-Square test does not provide definitive evidence of causal relationships or overall significance within the confirmatory factor analysis. The confirmatory factor analysis will involve more sophisticated statistical techniques to assess the fit of the proposed factor structure and determine the statistical significance of the latent constructs. Only after performing these tests can we draw concrete conclusions regarding the significance and relationships of the factors under investigation.

In summary, the Chi-Square test results highlight variables that demonstrate statistical significance with the response variable, thereby informing our subsequent confirmatory factor analysis. However, caution must be exercised in interpreting these results, as further analyses are necessary to establish the true significance and relationships within the latent constructs of interest.

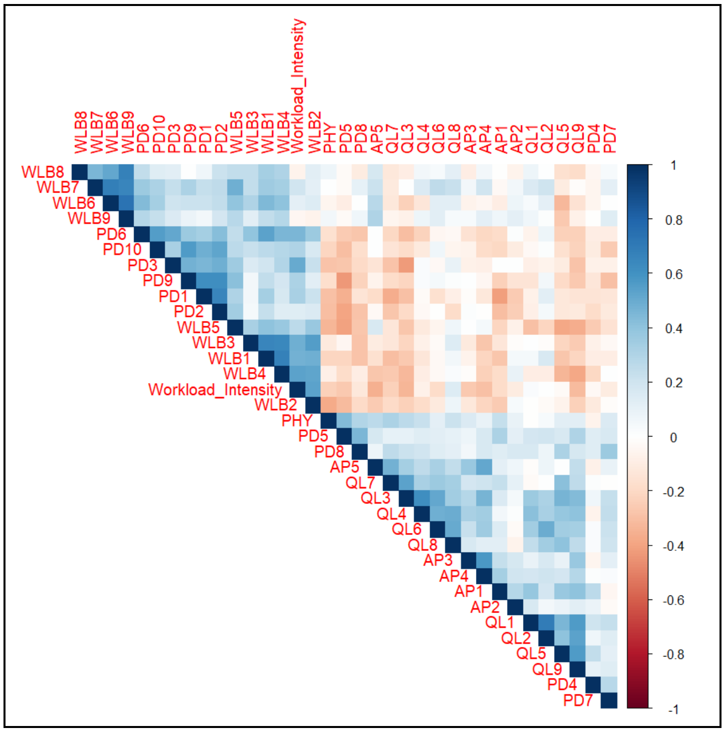


Fig. 2: Correlation Coefficient Matrix

Based on the correlation matrix presented above, it is evident that the variables associated with a specific factor, such as work-life balance (specifically WLB1 to WLB9), exhibit substantial and significant positive or negative correlation coefficients. This observation underscores the significance of employing dimensionality reduction techniques, such as Principal Component Analysis (PCA) and Factor Analysis (FA), in order to extract more meaningful and interpretable factors from our existing set of variables.

The strong positive or negative correlations among the variables within the work-life balance factor indicate that these variables tend to move together in a coordinated manner. This suggests that they capture similar aspects or dimensions related to work-life balance. By reducing the dimensionality of our dataset through techniques like PCA and FA, we can combine these highly correlated variables into a smaller set of uncorrelated factors or components that capture the essential information and underlying structure of the data.

By applying dimensionality reduction techniques like PCA and FA to our dataset, we can derive a reduced set of factors that capture the essence of the original variables and provide a more concise representation of the underlying phenomena. This process enables us to better interpret and analyze the data, uncover meaningful patterns and relationships, and facilitate further statistical modeling and inference.

```
> summary(data)
      Age           Gender     Academic_Standing                             College
 Min.   :18.0   Female:25   Freshman : 3      College of Arts and Sciences      :10
 1st Qu.:19.0   Male  :35   Junior   :12      College of Engineering            :44
 Median :20.0               Masters  : 3      School of Business Administration: 6
 Mean   :20.3               Senior   :16
 3rd Qu.:21.0               Sophomore:26
 Max.   :24.0
 Workload_Intensity Commuting PD1    PD2    PD3    PD4    PD5    PD6    PD7    PD8    PD9    PD10
 2: 2               No :14    0: 5   0: 5   0: 2   0: 1   0: 2   0: 2   0: 7   0: 3   0: 7   0: 2
 3:14               Yes:46    1:12   1:12   1: 5   1: 8   1: 9   1:12   1:10   1:19   1:11   1: 8
 4:28                         2:25   2:17   2:18   2:26   2:32   2:19   2:19   2:29   2:10   2:22
 5:16                         3:11   3:19   3:18   3:20   3:16   3:16   3:19   3: 9   3:24   3:14
                              4: 7   4: 7   4:17   4: 5   4: 1   4:11   4: 5          4: 8   4:14

 PHY    AP1    AP2    AP3    AP4    AP5    WLB1   WLB2   WLB3   WLB4   WLB5   WLB6   WLB7   WLB8
 1: 7   1: 4   1: 2   1: 9   1: 4   1: 5   1: 4   1: 4   1: 5   1: 8   1: 8   1:17   1:11   1:37
 2:11   2: 8   2:13   2: 6   2:11   2: 5   2:13   2: 9   2:12   2:15   2: 9   2:14   2:13   2: 4
 3:16   3:29   3:23   3:25   3:24   3:18   3:11   3:10   3:11   3:14   3:15   3:11   3:15   3:11
 4:17   4:14   4:18   4:16   4:17   4:18   4:22   4:20   4:22   4:13   4:21   4:16   4:15   4: 8
 5: 9   5: 5   5: 4   5: 4   5: 4   5:14   5:10   5:17   5:10   5:10   5: 7   5: 2   5: 6

 WLB9   QL1    QL2    QL3    QL4    QL5    QL6    QL7    QL8    QL9    Satisfaction
 1:29   1: 1   2: 7   2: 4   1: 2   2: 6   1: 2   1: 1   2: 6   1: 3   1: 1
 2:13   2: 8   3:22   3:18   2:10   3:11   2: 2   2:11   3:19   2: 5   2: 5
 3: 5   3:20   4:25   4:26   3:22   4:24   3:23   3:14   4:23   3:14   3:13
 4:11   4:21   5: 6   5:12   4:22   5:19   4:25   4:27   5:12   4:26   4:23
 5: 2   5:10                 5: 4          5: 8   5: 7          5:12   5:18

>
```

Fig 3: Summary of the data after cleaning

After the meticulous process of data cleaning, we now have the opportunity to examine the distribution and statistical characteristics of the variables present in our dataset, as depicted in the provided visualizations and summary statistics. These findings not only validate our prior knowledge about the population statistics but also verify that our data is suitably prepared for subsequent implementation of Principal Component Analysis (PCA) and Factor Analysis (FA) using our designated source code.

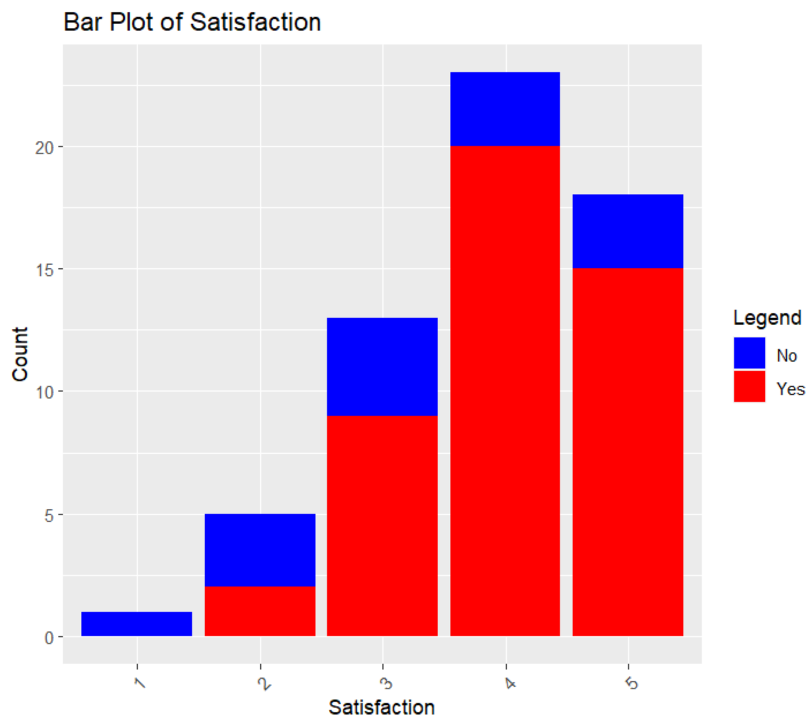


Fig 4: Distribution of Satisfaction based on whether the student commutes to university

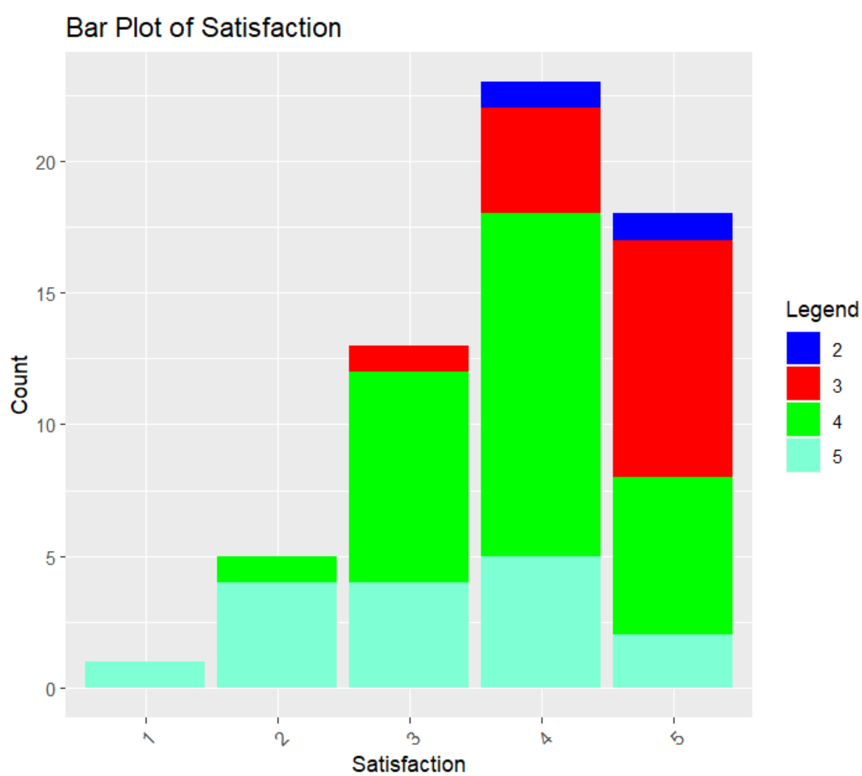


Fig 5: Distribution of Satisfaction based on workload intensity

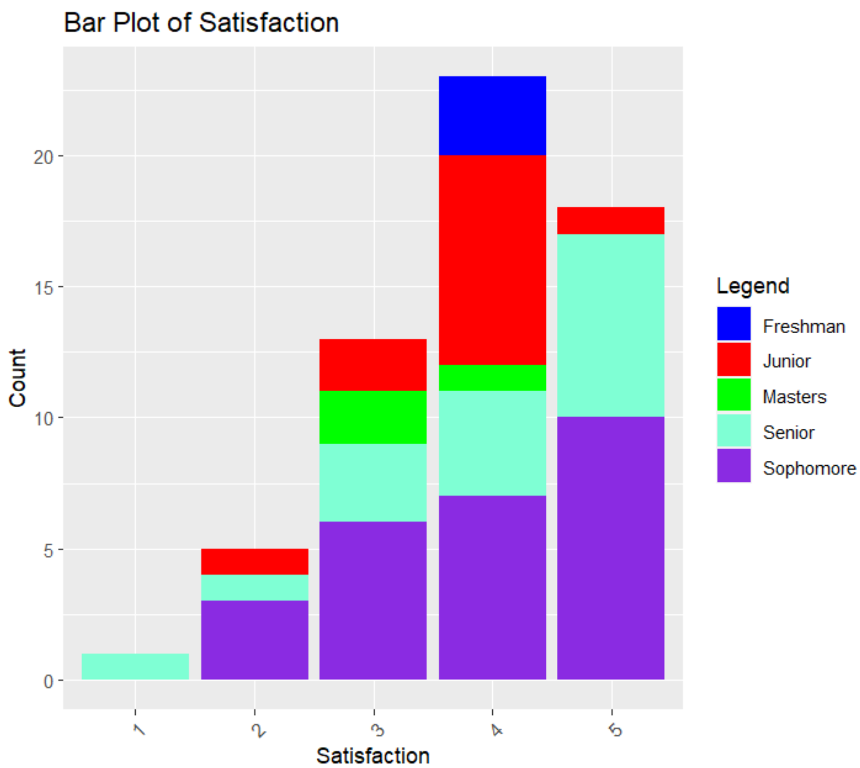


Fig 6: Distribution of Satisfaction based on academic standing

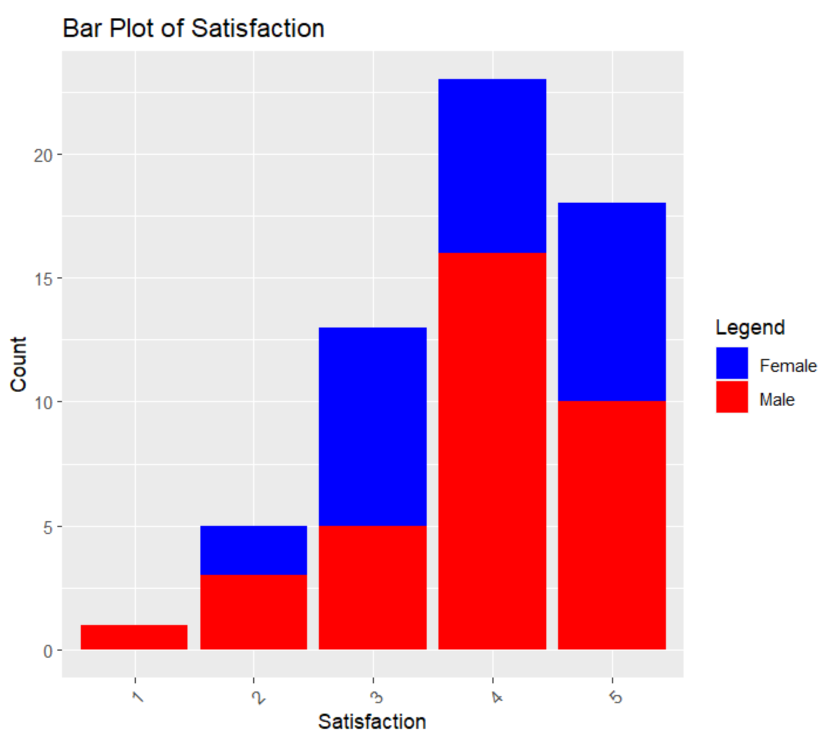


Fig 7: Distribution of Satisfaction based on gender

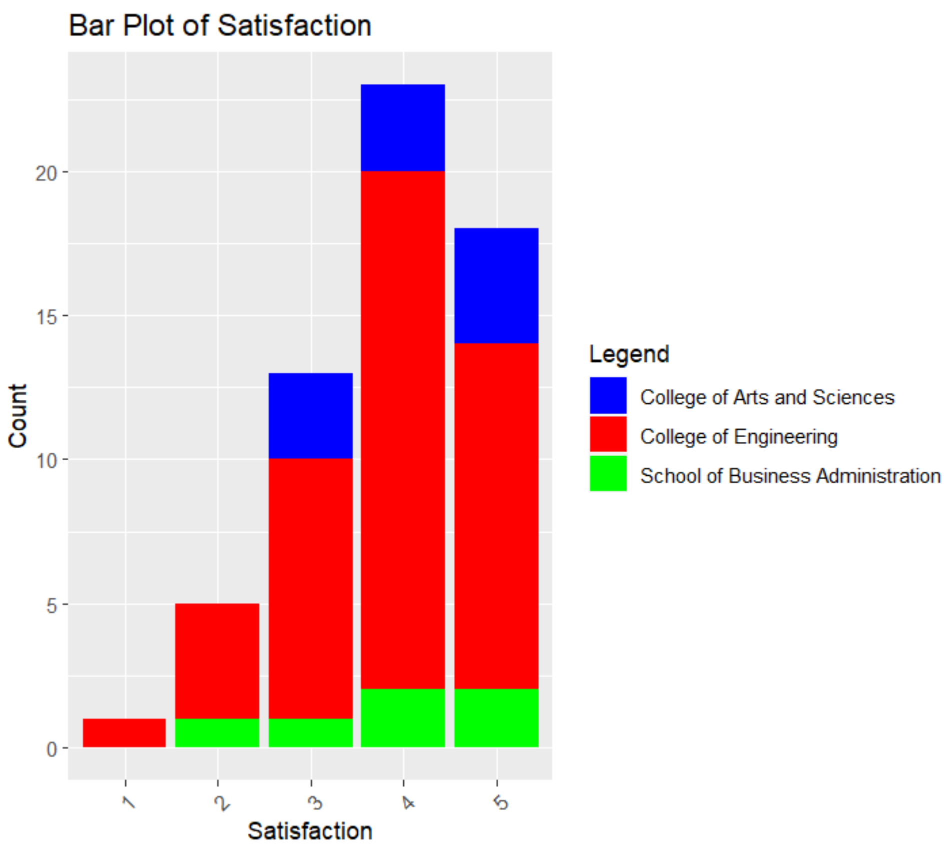


Fig 8: Distribution of Satisfaction based on college

Based on the above bar plots, we can conclude the following trends between the demographics of our survey respondents and our response variable:

- *Commuting*: We observe very minimal impact of this factor on our response variable. However, we do observe that all negative responses received mainly originated from students that did not commute. This observation could be explained by the fact that most commuting students prefer the 4-day working week system due to the lower aggregate costs and time for their commute to university. Hence, we can conclude that the 4-day working week is beneficial to students that live outside of campus.
- *Workload Intensity*: We observe a moderate impact of this factor on our response variable. A large portion of the positive responses mainly originate from students with a lower workload. This observation can be attributed to the fact that a lower university workload would generally lead to less stress amongst students, thereby increasing their satisfaction levels. However, students with a larger workload did not necessarily exhibit lower levels of satisfaction, and we can see an even distribution amongst the survey respondents. This observation seems to suggest

that higher workloads may not be the only cause of lower satisfaction, and various external factors influence the satisfaction level of university students.

- *Academic Standing*: We observe a minimal impact of this factor on our response variable. Underclassmen such as freshmen and sophomores generally seemed to possess higher levels of satisfaction. This observation can be explained due to the lower level of courses and workload during these years. However, upperclassmen showed an even distribution of satisfaction levels. This observation can be explained due to the fact that upperclassmen either adapt or fail to adapt to the heavier workload. Hence, we cannot conclude a significant relationship between academic standing and satisfaction.
- *Gender*: We observe no impact of this factor on our response variable. We see an equal distribution of males and females among the various satisfaction levels. This observation falls in line with our predictions, and hence we can conclude no relationship between gender and satisfaction.
- *College*: We observe a moderate impact of this factor on our response variable. Students in the College of Arts and Sciences (CAS) seemed to have a higher level of satisfaction as compared to students in the College of Engineering (CEN) and School of Business Administration (SBA). CEN and SBA students showed an even distribution of satisfaction levels suggesting that they weren't heavily impacted by the 4-day working week. CAS majors may have satisfaction levels with the 4-day working week due to some unknown factors that were beyond the scope of this project.

```
> #Tests on variables
> bart_spher(data_var)

        Bartlett's Test of Sphericity

Call: bart_spher(x = data_var)

     X2 = 1131.302
     df = 561
p-value < 2.22e-16

> KMO(data_var)
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = data_var)
Overall MSA =  0.66
MSA for each item =
 PD1  PD2  PD3  PD4  PD5  PD6  PD7  PD8  PD9 PD10  PHY  AP1  AP2  AP3  AP4  AP5 WLB1 WLB2 WLB3 WLB4 WLB5 WLB6 WLB7
0.71 0.67 0.52 0.52 0.67 0.65 0.38 0.58 0.71 0.60 0.63 0.53 0.46 0.64 0.54 0.50 0.77 0.75 0.75 0.77 0.70 0.67 0.66
WLB8 WLB9  QL1  QL2  QL3  QL4  QL5  QL6  QL7  QL8  QL9
0.64 0.74 0.69 0.70 0.81 0.63 0.76 0.67 0.70 0.63 0.68
>
```

Fig 9: Results of Barlett's test and KMO test

Our dataset underwent two crucial statistical tests, namely Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) factor adequacy test, to evaluate its suitability for factor analysis. The results of these tests, summarized above, provide valuable insights into the interrelationships among the variables and the overall adequacy of the dataset for factor analysis.

Bartlett's test of sphericity is a significance test employed in factor analysis to assess whether the correlation matrix exhibits a spherical shape. It examines the hypothesis that the variables in the dataset are uncorrelated, indicating unsuitability for factor analysis. In our analysis, the obtained p-value is less than the conventional significance level of 0.05, which leads us to reject the null hypothesis. Consequently, Bartlett's test indicates the presence of statistically significant intercorrelations among the variables in our dataset, providing evidence in favor of conducting factor analysis.

On the other hand, the KMO test evaluates the sampling adequacy of the observed variables for extracting meaningful factors in factor analysis. It measures the degree to which the variables share common variance and can be appropriately used for factor analysis. In our assessment, the KMO test yielded a measure of sampling adequacy (MSA) value exceeding 0.6, which suggests that the variables in our dataset are acceptably sampled for factor analysis. This finding strengthens our confidence in the suitability of the dataset for conducting factor analysis.

Based on the outcomes of both Bartlett's test and the KMO test, we can confidently conclude that our dataset exhibits significant intercorrelations among the variables and demonstrates adequate sampling adequacy. These results support the use of factor analysis as a suitable approach to extract meaningful factors from our dataset. This information is crucial for subsequent analyses and interpretations that rely on the derived factors to gain insights into the underlying structures and relationships within the data.

B. Principal Component Analysis

```
> pca_result <- prcomp(data_var)
> summary(pca_result)
Importance of components:
                          PC1    PC2     PC3     PC4     PC5    PC6     PC7     PC8     PC9    PC10    PC11
Standard deviation     3.0434 2.2897 1.85061 1.69874 1.45657 1.2930 1.25953 1.19477 1.12564 1.05805 1.02411
Proportion of Variance 0.2338 0.1323 0.08645 0.07284 0.05355 0.0422 0.04004 0.03603 0.03198 0.02826 0.02647
Cumulative Proportion  0.2338 0.3661 0.45257 0.52541 0.57896 0.6212 0.66120 0.69723 0.72922 0.75747 0.78395
                          PC12    PC13    PC14   PC15   PC16    PC17    PC18    PC19    PC20    PC21    PC22
Standard deviation     0.93640 0.90158 0.85364 0.8182 0.8061 0.75491 0.74445 0.71417 0.67562 0.62807 0.59448
Proportion of Variance 0.02213 0.02052 0.01839 0.0169 0.0164 0.01438 0.01399 0.01287 0.01152 0.00996 0.00892
Cumulative Proportion  0.80608 0.82660 0.84499 0.8619 0.8783 0.89267 0.90666 0.91954 0.93106 0.94102 0.94994
                          PC23    PC24    PC25    PC26    PC27    PC28    PC29    PC30    PC31    PC32    PC33
Standard deviation     0.55857 0.50850 0.48561 0.44812 0.44090 0.40654 0.39760 0.34888 0.33258 0.29101 0.28421
Proportion of Variance 0.00788 0.00653 0.00595 0.00507 0.00491 0.00417 0.00399 0.00307 0.00279 0.00214 0.00204
Cumulative Proportion  0.95781 0.96434 0.97029 0.97536 0.98027 0.98444 0.98843 0.99150 0.99429 0.99643 0.99847
                          PC34
Standard deviation     0.24628
Proportion of Variance 0.00153
Cumulative Proportion  1.00000
>
```

Fig 10: Results of PCA

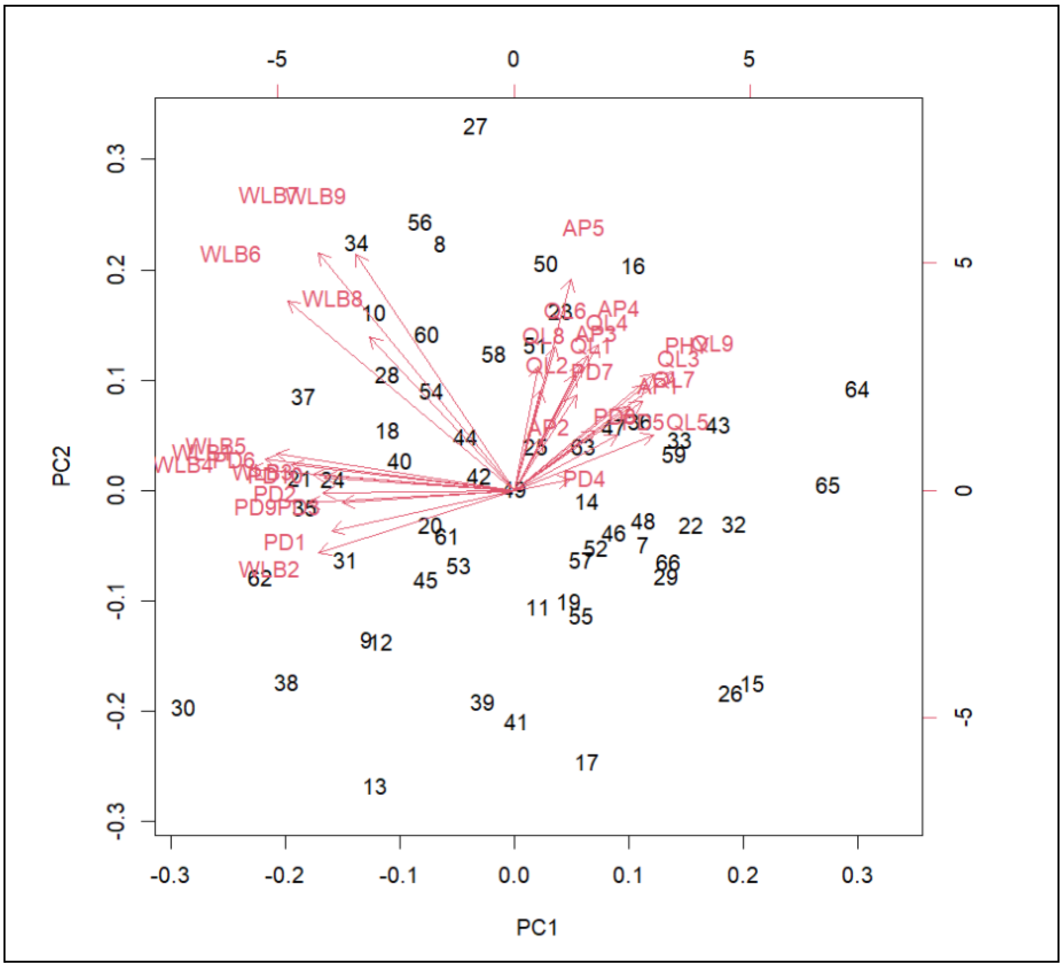


Fig 11: BiPlot of PCA loadings

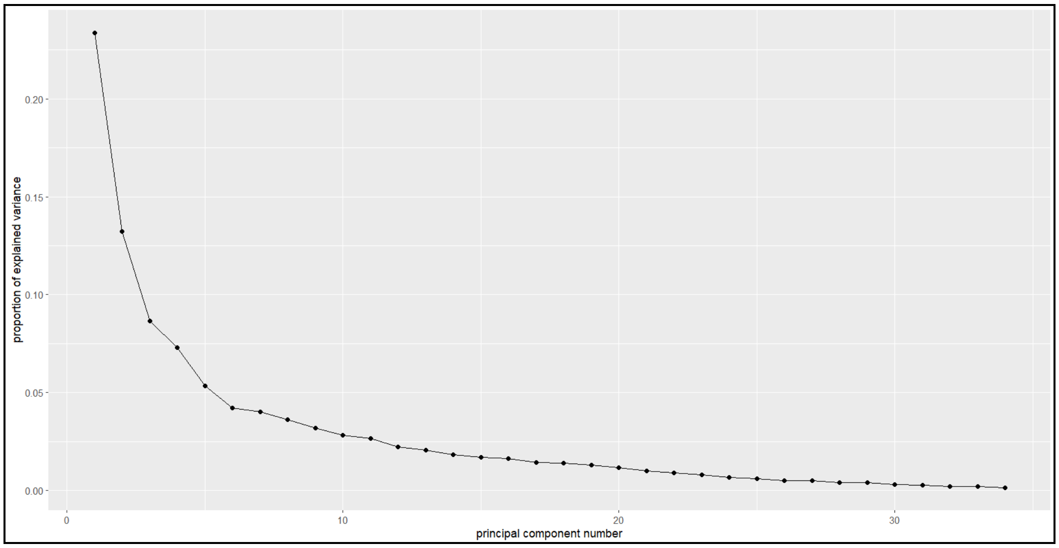


Fig 12: Scree Plot of principal components and proportion of explained variance

The scree plot above does not show a clear elbow, however around 50% of the variance of the data could be explained by the first 5 PC's. Therefore, we ran an ordinal logistic regression model on them.

Ordinal Logistic Regression on first 5 PCs

```
> summary(pca_model)
Call:
polr(formula = data$Satisfaction ~ pca_scores[, 1] + pca_scores[,
    2] + pca_scores[, 3] + pca_scores[, 4] + pca_scores[, 5],
    Hess = TRUE)

Coefficients:
                   Value Std. Error t value
pca_scores[, 1]  0.40195    0.09841  4.0844
pca_scores[, 2]  0.22497    0.11693  1.9239
pca_scores[, 3] -0.14199    0.13598 -1.0442
pca_scores[, 4]  0.20350    0.15126  1.3454
pca_scores[, 5]  0.07211    0.17796  0.4052

Intercepts:
    Value   Std. Error t value
1|2 -4.9075  1.0700    -4.5866
2|3 -2.7981  0.4988    -5.6098
3|4 -1.0121  0.3329    -3.0400
4|5  1.2291  0.3389     3.6266

Residual Deviance: 134.864
AIC: 152.864
```

Fig 13: Results of Logistic Regression using PCA loadings

From the logistic regression summary, it is clear that the fifth PC does not really contribute to the model. However, it is not possible to interpret the PCs and their correlation with the original variables. For this reason, factor analysis was used.

C. Exploratory Factor Analysis (EFA)

We first ran EFA using 34 (total) factors in order to assess which ones are significant and which ones aren't. Using Kaiser's rule, we found that there were around 16 significant factors, with eigenvalues of magnitude larger than 1. Moreover, a scree plot was obtained to show how many factors are really necessary for this analysis. The scree plot was similar to the one obtained in PCA, and so we decided to go ahead and use 5 factors for EFA.

	MR4	MR13	MR2	MR1	MR25	MR18	MR29	MR30	MR5	MR3	MR8	MR23	MR6	MR11	MR9
SS loadings	1.40	1.35	1.35	1.34	1.34	1.25	1.21	1.20	1.19	1.19	1.15	1.12	1.08	1.06	1.05
Proportion Var	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03
Cumulative Var	0.04	0.08	0.12	0.16	0.20	0.24	0.27	0.31	0.34	0.38	0.41	0.44	0.48	0.51	0.54
Proportion Explained	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03
Cumulative Proportion	0.05	0.09	0.13	0.18	0.22	0.26	0.30	0.34	0.38	0.42	0.45	0.49	0.53	0.56	0.60
	MR16	MR10	MR7	MR12	MR20	MR32	MR21	MR14	MR19	MR27	MR26	MR33	MR22	MR17	MR31
SS loadings	1.04	0.99	0.99	0.96	0.96	0.79	0.74	0.73	0.62	0.60	0.55	0.53	0.52	0.52	0.51
Proportion Var	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Cumulative Var	0.57	0.60	0.63	0.65	0.68	0.71	0.73	0.75	0.77	0.79	0.80	0.82	0.83	0.85	0.86
Proportion Explained	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Cumulative Proportion	0.63	0.66	0.69	0.72	0.76	0.78	0.81	0.83	0.85	0.87	0.89	0.90	0.92	0.94	0.96
	MR28	MR24	MR15	MR34											
SS loadings	0.49	0.46	0.43	0.0											
Proportion Var	0.01	0.01	0.01	0.0											
Cumulative Var	0.88	0.89	0.90	0.9											
Proportion Explained	0.02	0.01	0.01	0.0											
Cumulative Proportion	0.97	0.99	1.00	1.0											

Fig 14: Factor Analysis loading values

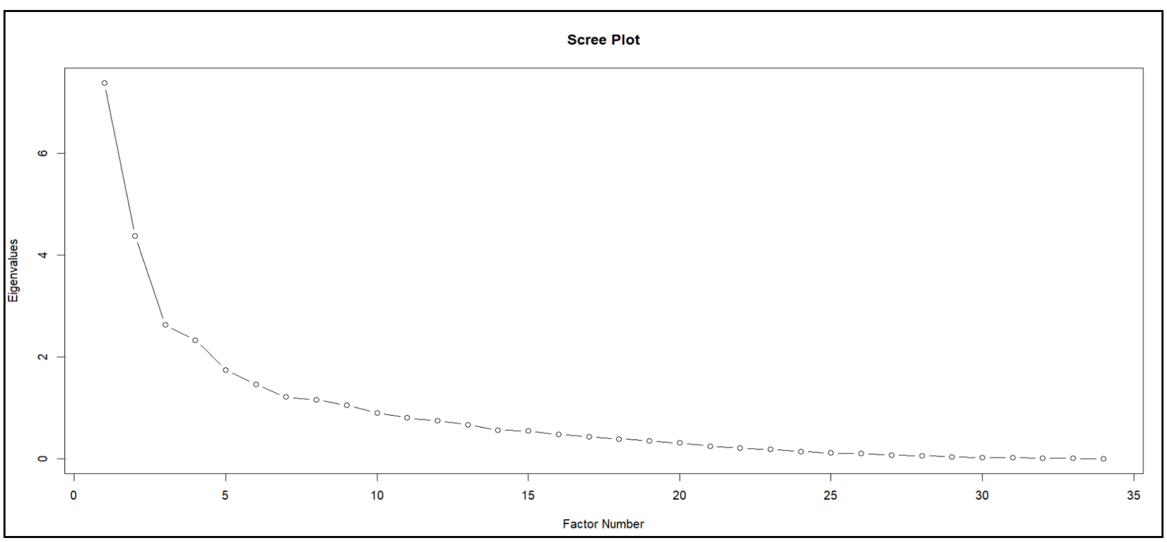


Fig 15: Scree Plot of factors and proportions of explained variance

EFA using 5 Factors

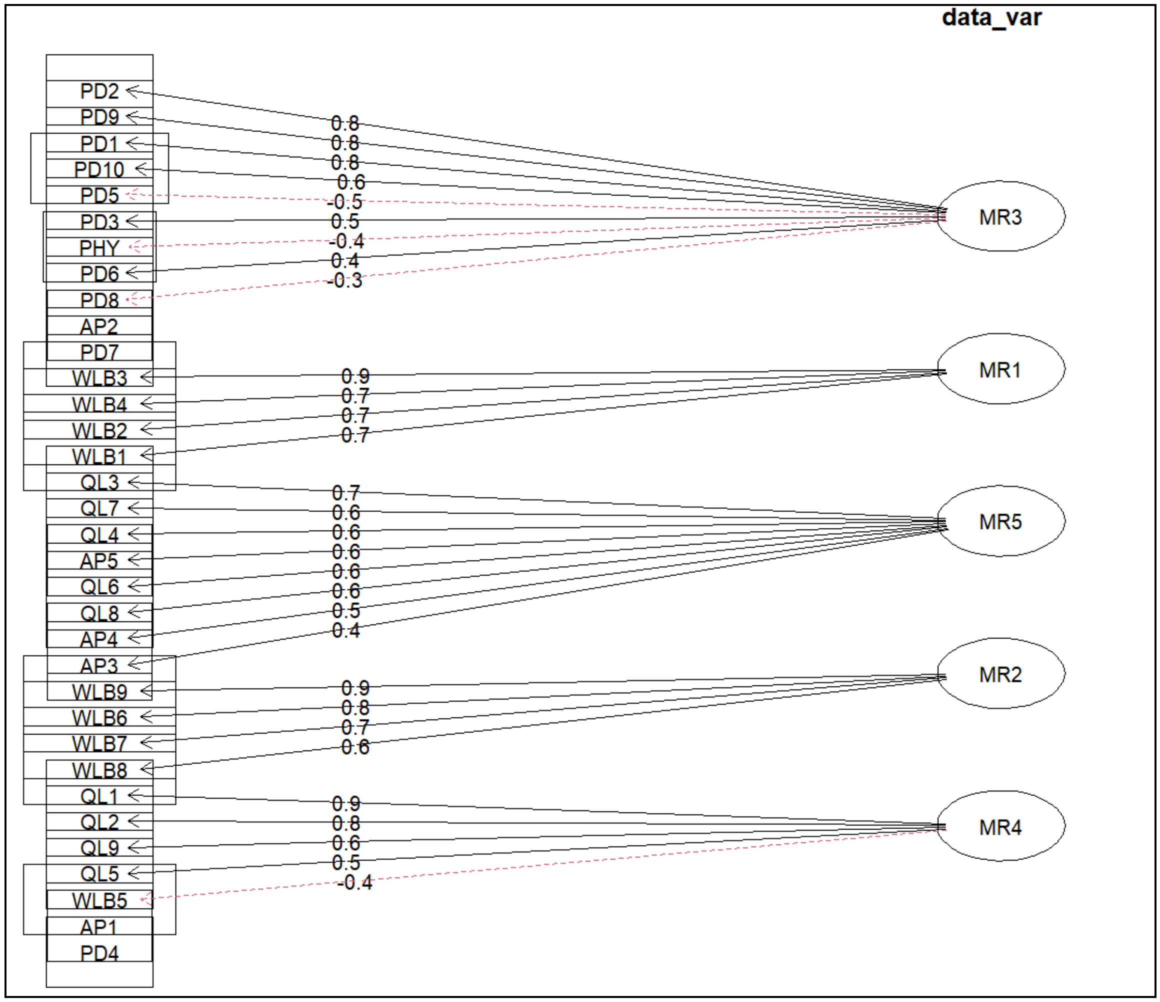


Fig 16: Factor Diagram for 5 factors

Interesting results could be drawn from this analysis. The first one being that the physical activity variable was clustered with the psychological distress variables. Additionally, the model was able to successfully cluster each variable according to the section/factor that it belongs to. MR4 and MR3 successfully clustered the quality of learning and the psychological distress variables together respectively. MR1 and MR2 clustered the work-life balance variables correctly as well, in which WLB 1-4 and WLB 6-9 are separated into two factors, which we intended to do so later on. As per the academic performance variables, they seem to be dispersed and distributed among the factors, hence we were not able to draw any conclusions from this analysis regarding this factor. Below is the output of the exploratory factor analysis.

```
                       MR3  MR1  MR5  MR2  MR4
SS loadings           4.00 3.33 3.25 3.11 3.00
Proportion Var        0.12 0.10 0.10 0.09 0.09
Cumulative Var        0.12 0.22 0.31 0.40 0.49
Proportion Explained  0.24 0.20 0.19 0.19 0.18
Cumulative Proportion 0.24 0.44 0.63 0.82 1.00

 With factor correlations of 
      MR3   MR1   MR5   MR2   MR4
MR3  1.00  0.29 -0.15  0.21 -0.11
MR1  0.29  1.00 -0.20  0.24 -0.08
MR5 -0.15 -0.20  1.00  0.09  0.27
MR2  0.21  0.24  0.09  1.00 -0.03
MR4 -0.11 -0.08  0.27 -0.03  1.00

Mean item complexity =  1.8
Test of the hypothesis that 5 factors are sufficient.

df null model =  561  with the objective function =  24.16 with Chi Square =  1131.3
df of  the model are 401  and the objective function was  9.5 

The root mean square of the residuals (RMSR) is  0.06 
The df corrected root mean square of the residuals is  0.07 

The harmonic n.obs is  60 with the empirical chi square  254.94  with prob <  1 
The total n.obs was  60  with Likelihood Chi Square =  413.11  with prob <  0.33 

Tucker Lewis Index of factoring reliability =  0.965
RMSEA index =  0.015  and the 90 % confidence intervals are  0 0.052
BIC =  -1228.72
Fit based upon off diagonal values = 0.94
Measures of factor score adequacy             
                                                   MR3  MR1  MR5  MR2  MR4
Correlation of (regression) scores with factors   0.95 0.94 0.93 0.96 0.94
Multiple R square of scores with factors          0.91 0.89 0.87 0.93 0.89
Minimum correlation of possible factor scores     0.82 0.78 0.74 0.86 0.78
```

Fig 17: Overall summary of results of EFA

D. Confirmatory Factor Analysis (CFA)

We ran a confirmatory factor analysis model on the data using the factors that were defined in the survey outline. All the variables were used in this initial analysis. As observed in the plots below, the standardized root mean square residual value was equal to 0.118, highlighting that the model is not satisfactory.

```
> #CFA, confirmatory
> model <- '
+ PD =~ PD1+PD2+PD3+PD4+PD5+PD6+PD7+PD8+PD9+PD10+PHY
+ AP =~ AP1+AP2+AP3+AP4+AP5
+ WLB1N=~WLB1+WLB2+WLB3+WLB4+WLB5
+ WLB2N=~WLB6+WLB7+WLB8+WLB9
+ QL=~QL1+QL2+QL3+QL4+QL5+QL6+QL7+QL8+QL9
+ '
> fit <-cfa(model, data=data_var)
> summary(fit,fit.measures=TRUE,standardized=TRUE)
```

Fig 18: Source code used for CFA

```
  Akaike (AIC)                                 5469.680
  Bayesian (BIC)                               5633.039
  Sample-size adjusted Bayesian (SABIC)        5387.708

Root Mean Square Error of Approximation:

  RMSEA                                           0.092
  90 Percent confidence interval - lower          0.079
  90 Percent confidence interval - upper          0.105
  P-value H_0: RMSEA <= 0.050                     0.000
  P-value H_0: RMSEA >= 0.080                     0.932

Standardized Root Mean Square Residual:

  SRMR                                            0.118

Parameter Estimates:

  Standard errors                              Standard
  Information                                  Expected
  Information saturated (h1) model           Structured
```

```
Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PD =~
    PD1               1.000                               0.803    0.739
    PD2               1.106    0.190    5.820    0.000    0.889    0.785
    PD3               0.814    0.180    4.529    0.000    0.654    0.613
    PD4              -0.214    0.149   -1.441    0.150   -0.172   -0.198
    PD5              -0.516    0.132   -3.904    0.000   -0.414   -0.531
    PD6               0.819    0.185    4.437    0.000    0.658    0.601
    PD7              -0.374    0.193   -1.941    0.052   -0.301   -0.266
    PD8              -0.355    0.131   -2.705    0.007   -0.285   -0.370
    PD9               1.168    0.207    5.645    0.000    0.938    0.761
    PD10              0.928    0.183    5.078    0.000    0.746    0.685
    PHY              -0.584    0.209   -2.797    0.005   -0.469   -0.382
  AP =~
    AP1               1.000                               0.388    0.399
    AP2               0.570    0.386    1.477    0.140    0.221    0.234
    AP3               1.813    0.680    2.667    0.008    0.704    0.634
    AP4               2.196    0.778    2.822    0.005    0.853    0.857
    AP5               1.826    0.697    2.620    0.009    0.709    0.603
  WLB1N =~
    WLB1              1.000                               0.973    0.824
    WLB2              0.801    0.158    5.053    0.000    0.779    0.635
    WLB3              0.964    0.149    6.458    0.000    0.938    0.777
    WLB4              1.090    0.158    6.879    0.000    1.060    0.821
    WLB5              0.624    0.163    3.841    0.000    0.607    0.500
  WLB2N =~
    WLB6              1.000                               1.054    0.847
    WLB7              0.932    0.136    6.842    0.000    0.982    0.780
    WLB8              0.737    0.130    5.692    0.000    0.777    0.680
    WLB9              1.035    0.134    7.747    0.000    1.091    0.864
  QL =~
    QL1               1.000                               0.594    0.609
    QL2               0.828    0.217    3.808    0.000    0.492    0.595
    QL3               1.059    0.236    4.491    0.000    0.629    0.746
    QL4               1.087    0.254    4.278    0.000    0.645    0.695
    QL5               1.051    0.255    4.119    0.000    0.624    0.660
    QL6               0.975    0.237    4.109    0.000    0.579    0.658
    QL7               0.779    0.246    3.170    0.002    0.463    0.475
    QL8               0.832    0.234    3.562    0.000    0.494    0.547
    QL9               1.197    0.284    4.210    0.000    0.711    0.680
```

Fig 19: Summary of EFA results using all factors

The standardized loadings for some of the psychological distress (PD) variables seem to be negatively correlated with the factor PD, and so we had to adjust their scaling in order to be in the same direction as the other variables. Moreover, after adjusting the scales of the negatively correlated variables, we then removed the insignificant variables. The way we assessed the significance of each variable was by looking at the standardized loading value of each variable in correspondence to the latent factor. Those with loading values below 0.6 were omitted. The analysis for the reduced model is shown below.

```
> #Transforming variable scales PD4, PD5, PD7, PD8
> data_var$PD4n=4-data_var$PD4
> data_var$PD5n=4-data_var$PD5
> data_var$PD7n=4-data_var$PD7
> data_var$PD8n=4-data_var$PD8
> data_var$PHYn=4-data_var$PHY
> #removing insignificant variables
> model3 <- '
+ PD =~ PD1+PD2+PD3+PD6+PD9+PD10
+ AP =~ AP3+AP4+AP5
+ WLB1N=~WLB1+WLB2+WLB3+WLB4
+ WLB2N=~WLB6+WLB7+WLB8+WLB9
+ QL=~QL1+QL2+QL3+QL4+QL5+QL6+QL9
+ '
> fit <-cfa(model3, data=data_var)
> summary(fit,fit.measures=TRUE,standardized=TRUE)
```

```
Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -1869.399
  Loglikelihood unrestricted model (H1)      -1695.500

  Akaike (AIC)                                3854.797
  Bayesian (BIC)                              3976.269
  Sample-size adjusted Bayesian (SABIC)       3793.844

Root Mean Square Error of Approximation:

  RMSEA                                          0.085
  90 Percent confidence interval - lower         0.064
  90 Percent confidence interval - upper         0.105
  P-value H_0: RMSEA <= 0.050                    0.005
  P-value H_0: RMSEA >= 0.080                    0.678

Standardized Root Mean Square Residual:

  SRMR                                           0.108

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured
```

```
Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PD =~
    PD1               1.000                               0.815    0.750
    PD2               1.094    0.187    5.846    0.000    0.892    0.787
    PD3               0.809    0.177    4.573    0.000    0.660    0.619
    PD6               0.817    0.182    4.490    0.000    0.666    0.608
    PD9               1.152    0.203    5.663    0.000    0.940    0.762
    PD10              0.931    0.180    5.177    0.000    0.759    0.698
  AP =~
    AP3               1.000                               0.699    0.630
    AP4               1.247    0.296    4.206    0.000    0.872    0.876
    AP5               1.020    0.267    3.822    0.000    0.713    0.607
  WLB1N =~
    WLB1              1.000                               0.967    0.819
    WLB2              0.796    0.161    4.948    0.000    0.770    0.628
    WLB3              0.986    0.152    6.507    0.000    0.954    0.791
    WLB4              1.105    0.162    6.829    0.000    1.069    0.828
  WLB2N =~
    WLB6              1.000                               1.054    0.847
    WLB7              0.933    0.136    6.858    0.000    0.983    0.782
    WLB8              0.736    0.129    5.684    0.000    0.776    0.679
    WLB9              1.034    0.134    7.742    0.000    1.090    0.863
  QL =~
    QL1               1.000                               0.681    0.699
    QL2               0.812    0.175    4.626    0.000    0.553    0.669
    QL3               0.852    0.180    4.743    0.000    0.580    0.687
    QL4               0.884    0.197    4.496    0.000    0.602    0.648
    QL5               0.901    0.200    4.498    0.000    0.614    0.649
    QL6               0.790    0.186    4.256    0.000    0.538    0.611
    QL9               1.124    0.224    5.012    0.000    0.765    0.732
```

Fig 20: Summary of EFA results using chosen factors

Clearly, the SRMR decreased to 0.108, which is close to 10% and so is within acceptable limits.

E. Ordinal Logistic Regression Models

Lastly, based on the latent factors that were obtained using CFA, we ran an ordinal logistic regression model. The purpose of this model is purely for inference on how the latent factors affect the response variable. The results for this model are shown below.

```
Call:
polr(formula = data$Satisfaction ~ data_var$PD + data_var$AP +
    data_var$WLB1N + data_var$WLB2N + data_var$QL, Hess = TRUE)

Coefficients:
                  Value Std. Error t value
data_var$PD    -0.61924     0.2952 -2.0978
data_var$AP     0.16266     0.2651  0.6135
data_var$WLB1N -0.48776     0.2463 -1.9804
data_var$WLB2N  0.04884     0.2438  0.2004
data_var$QL     0.52158     0.3322  1.5700

Intercepts:
    Value   Std. Error t value
1|2 -5.1963  1.9304    -2.6918
2|3 -3.1078  1.7153    -1.8118
3|4 -1.4117  1.6922    -0.8342
4|5  0.5920  1.6718     0.3541

Residual Deviance: 141.9853
AIC: 159.9853
```

Fig 21: Results of constructed Logistic Regression model

As seen from the results above, the factors that have the most impact on the satisfaction with the four day workweek shift happened to be psychological distress, work-life balance and quality of learning. The psychological distress factor has a strong negative correlation with the response variable. The scale of this factor was constructed in which 0 (never) - 4 (very often) corresponds to how often a person experiences psychological distress. Therefore, the logistic regression model tells us that higher levels of psychological distress usually corresponds to lower levels of satisfaction among university students, and vice versa; which is quite logical. Similarly, a part of the work-life balance factor has a strong negative correlation with the response variable. The survey questions in this factor tested two parts of work-life balance, mainly work-family conflict and family-work conflict. The scale of this factor lies between 1 (strongly disagree) and 5 (strongly agree), where each value corresponds to how severely university commitments affect family life. Hence, the model tells us that if students are unable to manage their family commitments due to their university commitments, they tend to possess lower levels of satisfaction, and vice versa. This conclusion falls in line with our expected outcome, and confirms our hypothesis. As per the quality of learning factor, it has a strong positive correlation with the response variable, which tells us that improving the quality of learning corresponds to higher levels of satisfaction with the workweek shift.

We generated plots that summarize the findings above for ease of visualization. The plots show the relative distribution of student satisfaction while taking into account the responses for the psychological distress, work-life balance and quality of learning factors. The legend on the right of the plots corresponds to student satisfaction from 1-5.

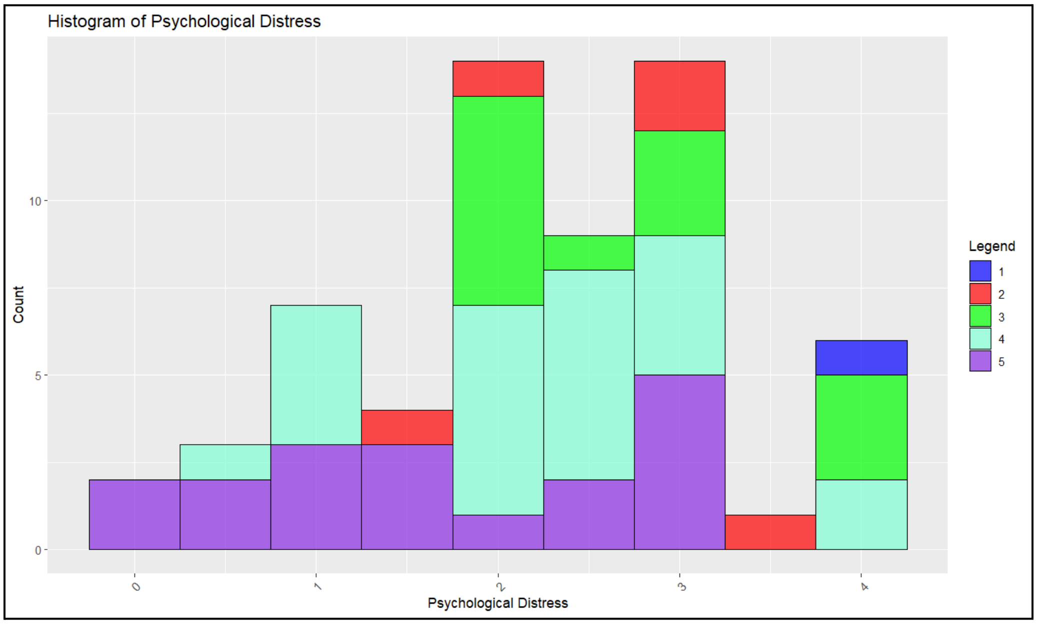


Fig 22: Histograms showing the distribution of Psychological Distress with respect to the satisfaction

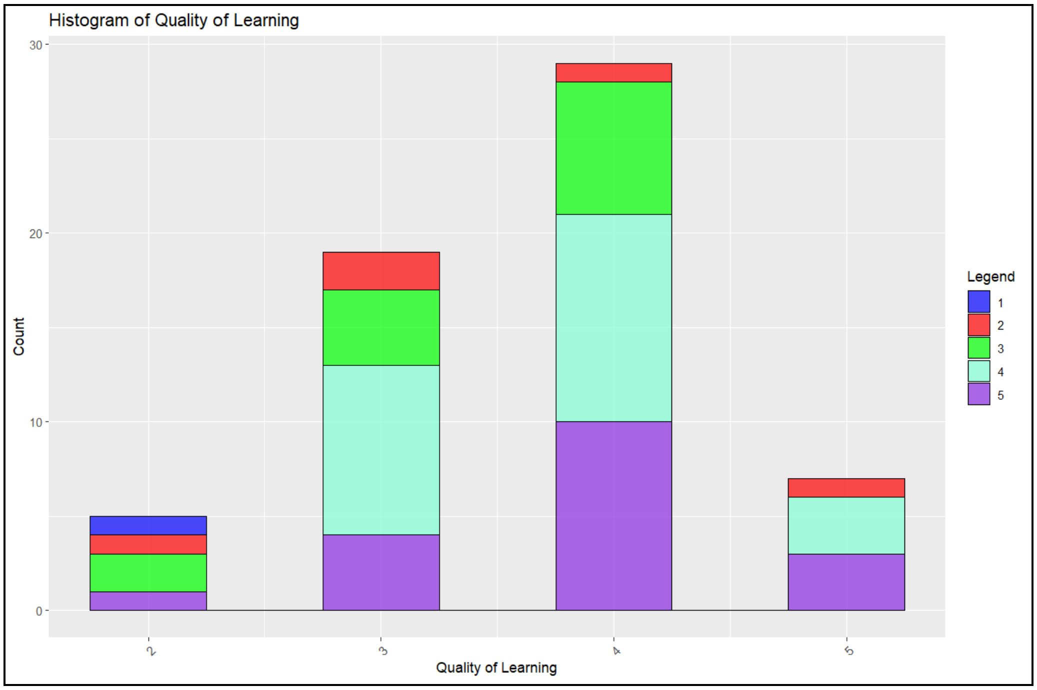


Fig 23: Histograms showing the distribution of Quality of Learning with respect to the satisfaction

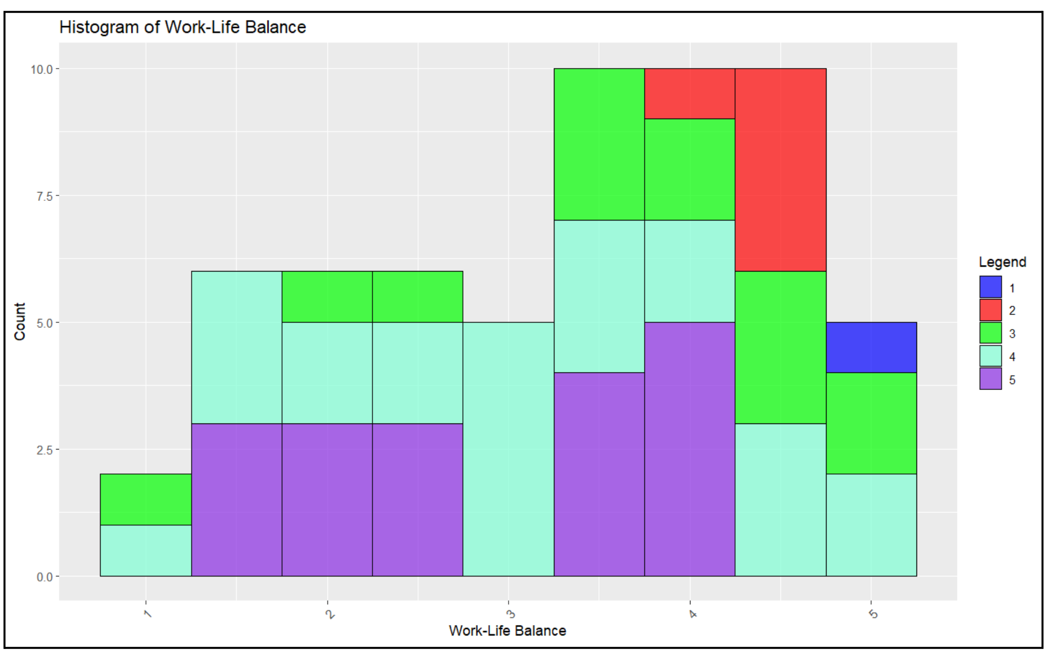
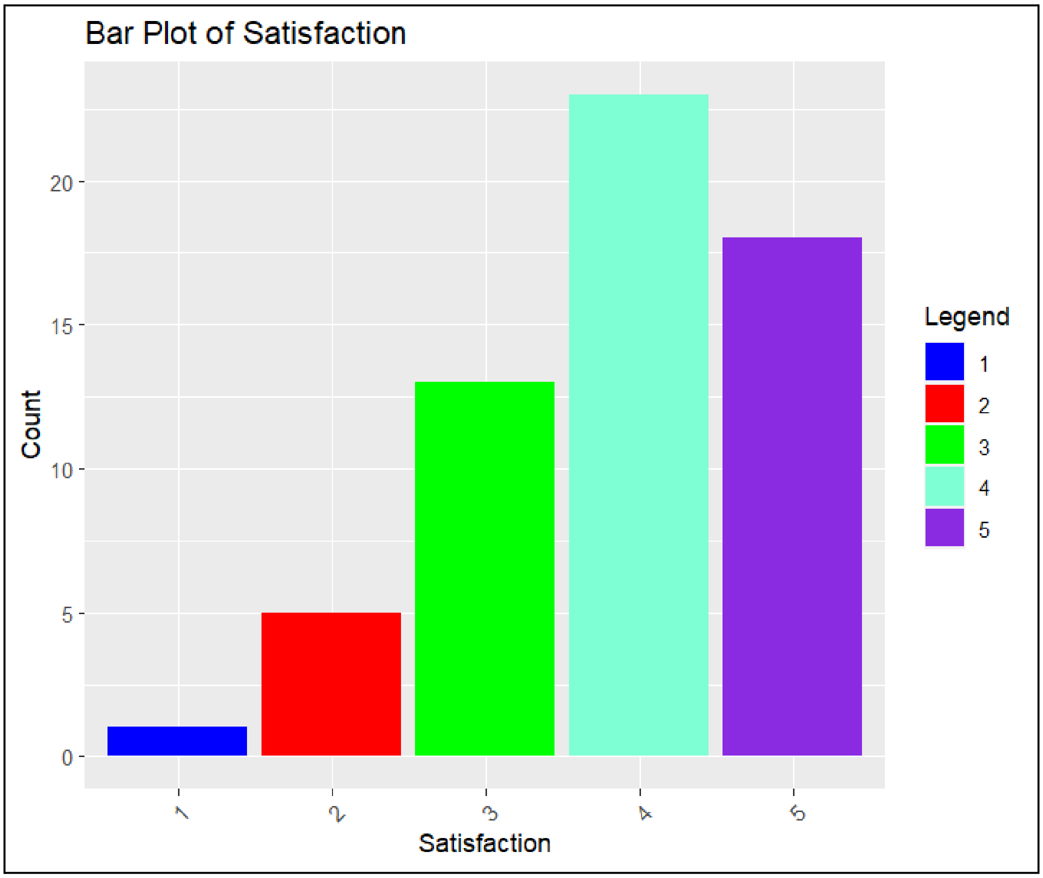


Fig 24: Histograms showing the distribution of Work-Life Balance with respect to the satisfaction

By looking at the distribution of the response variable once again, we can see that it is skewed to the left, leaning more towards higher levels of satisfaction with the workweek shift. By comparing this to the logistic regression model, we can conclude that the four day workweek shift has been successful so far and students are quite satisfied with it. Meaning that, there is not much psychological distress associated with the four day workweek shift. Similarly, students are able to spend more time with their families and experience an enhanced quality of learning.



V. CONCLUSION

This study looks at how a four-day work week affects student satisfaction with relation to things like psychological discomfort, learning quality, and work-life balance. Data from a survey of a sample of students at the American University of Sharjah were analyzed for the study. The main factors are initially identified using PCA and CFA. The impact of the four-day work week on student satisfaction was evaluated using an Ordinal Logistic Regression model based on the identified factors. It was observed that the intensity of psychological distress, amount of quality time spent with family and quality of learning have a strong effect on students' satisfaction with the four day workweek shift. It was found that students experienced psychological distress less often, were able to spend more time with their families in addition to experiencing an improved quality of learning in their classrooms. This research paper contributes to the existing literature on the impact of a four-day work week specifically in an educational context.

VI. REFERENCES

[1] Happiest countries in the world 2023, n.d. https://worldpopulationreview.com/country-rankings/happiest-countries-in-the-world.

[2] “Countries with a 4 Day Work Week.” Countries with a 4 Day Work Week, n.d. https://4dayweek.io/countries.

[3] “Sharjah announces four-day working week for public sector,” Arabian Business, Dec. 09, 2021.https://www.arabianbusiness.com/politics-economics/sharjah-announces-four-day-working-week-for-public-sector

[4] O. Kelly, J. Schor, W. Fan, T. Bezdenezhnykh, G. Gu, and N. Bridson, “The Four Day Week: Assessing global trials of reduced work time with no reduction in pay: Evidence from Ireland,” Jan. 2022.

[5] Cuello, H., Assessing the validity of four-day week pilots, European Commission, Seville, 2023, JRC133008.

[6] Loftin, Josh. “Utah Ends 4-Day Workweek Experiment, but Provo Says It Still Works for Them.” Utah Business Politics, September 5, 2011. https://www.deseret.com/2011/9/5/20387145/utah-ends-4-day-workweek-experiment-but-provo-says-it-still-works-for-them.

[7] D. M. Anderson and M. B. Walker, “Does Shortening the School Week Impact Student Performance? Evidence from the Four-Day School Week,” Education Finance and Policy, vol. 10, no. 3, pp. 314–349, Jul. 2015, doi: https://doi.org/10.1162/edfp_a_00165.

[8] “UAE Studies 3-Day Weekend for Schools - Arabian Business.” UAE studies 3-day weekend for schools, April 24, 2023. https://www.arabianbusiness.com/industries/education/uae-studies-3-day-weekend-for-schools.

[9] White, Casey B. PhD; Haftel, Hilary M. MD, MHPE; Purkiss, Joel A. PhD; Schigelone, Amy S. PhD; Hammoud, Maya M. MD. Multidimensional Effects of the 80-Hour Work Week at the University of Michigan Medical School. Academic Medicine 81(1):p 57-62, January 2006.

[10] Fang, Yu, Sara Lodi, Tasha M. Hughes, Elena Frank, Srijan Sen, and Amy S.B. Bohnert. “Work Hours and Depression in U.S. First-Year Physicians.” *New England Journal of Medicine* 387, no. 16 (2022): 1522–24. https://doi.org/10.1056/nejmc2210365.

[11] Hegarty, Dr David. “Perceived Stress Scale (PSS-10).” Perceived Stress Scale (PSS-10), March 2, 2023. https://novopsych.com.au/assessments/well-being/perceived-stress-scale-pss-10/.

[12] Haslam, D., Filus, A., Morawska, A., Sanders, M. R., & Fletcher, R. (2015). The work–family conflict scale (WAFCS): Development and initial validation of a self-report measure of work–family conflict for use with parents. Child Psychiatry and Human Development, 46(3), 346-357. doi: 10.1007/s10578-014-0476-0

[13] Student Experience Questionnaire, n.d. https://oirp.carleton.ca/teforms/Student%20Experience%20Questionnaire.pdf.

APPENDIX

Survey Outline

Item	Item Details
General Questions	
G1	Age
G2	Gender
G3	Academic Standing
G4	College
G5	Major
G6	During this semester, how strenuous is your workload?
G7	Do you commute to university?
G8	If you answered yes to the previous question, please highlight the average distance of your commute.
Psychological Distress - using Perceived Stress Scale (PSS) [11]	
	Since the shift to the 4 day working week, how often have you
P1	been upset because of something that happened unexpectedly?
P2	felt that you were unable to control the important things in your life?
P3	felt nervous and "stressed"?
P4	felt confident about your ability to handle your personal problems?
P5	felt that things were going your way?
P6	found that you could not cope with all the things that you had to do?
P7	been able to control irritations in your life?
P8	felt that you were on top of things?
P9	been angered because of things that were outside of your control?
P10	felt difficulties were piling up so high that you could not overcome them?
Physical Health	
	Highlight the extent to which you agree with the following statement:
PHY	Since the shift to the 4 day working week, I have more time to engage in physical activity exercises.
Academic Performance	
	Since the shift to the 4 day working week, highlight whether:
A1	your CGPA has increased.
A2	your time management skills have increased.
A3	your concentration has increased.
A4	your level of engagement in class has increased.
A5	your university attendance has increased.
Work - Life Balance [12] - scored out of 5	
	Since the shift to the 4 day working week, highlight the extent to which you agree with the following statements:
Work-family conflict	

W1	My academics prevented me from spending quality time with my family.
W2	There seems to be no time left at the end of each day to do things I'd like at home.
W3	My family misses out because of my university commitments.
W4	My university commitments have a negative impact on my family life.
W5	Working often makes me irritable or short tempered at home.

Family-work conflict

W6	My university performance suffers because of my family commitments.
W7	Family related concerns/responsibilities often distract me at university.
W8	If I did not have a family I'd be a better student.
W9	It is difficult to focus on university since I am exhausted by family responsibilities.

Quality of Learning [13]

	Since the shift to the 4 day working week, highlight the extent to which you agree with the following statements:
Q1	The learning outcomes of my courses are relevant and applicable to my future career or academic goals.
Q2	The courses I am taking help me acquire the necessary skills and knowledge for my future career or academic goals.
Q3	The instructors in my courses provide clear explanations and examples.
Q4	The teaching methods used in my courses are effective and engaging.
Q5	The instructors in my courses are approachable and available for help outside of class.
Q6	The assessments used in my courses are aligned with the learning outcomes and effectively measure my knowledge and skills.
Q7	The grading and evaluation process in my courses is fair and consistent.
Q8	I feel appropriately challenged and intellectually stimulated in my courses.
Q9	I feel supported by my instructors and peers in my courses.

Overall Satisfaction

O1	Overall, how satisfied are you with the shift from the 5 day work week to the 4 day work week?