

# **Analysis of Surgically Assisted Rapid Palatal Expansion (SARPE) Study**

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## Abstract

In this paper, we analyzed the Surgically Assisted Rapidly Palatal Plane (SARPE) study. The SARPE was performed to make an upper jaw of the patients more wider or become normal. The purpose of the study is to observe the changes in the Palatal Plane-Sella Nasion Plane (PP-SN) of patients before and after the SARPE and also to predict the (PP-SN) angle post jaw surgery based on the characteristics patients.

The data contains over 50 patients who underwent a SARPE procedure. The paired *t*-test was performed to see the changes of angle PP-SN before and post SARPE surgery. Regression linear analysis, regression tree and random forest were carried to investigate the effect of patients' characteristics (PP-SN pre surgery, age, gender and occlusion type) on the PP-SN post surgery.

The exploratory data analysis showed that from pre- to post surgery, more than half of the patients (e.g., 58%) have a higher PP-SN angle post surgery than before. It is shown from *t*-paired test the changes of PP-SN angle before to post surgery was significant. From regression linear, we discover that PP-SN pre surgery angle and gender have a significant relationship with the PP-SN post surgery. Regression tree and random forest showed that PP-SN pre surgery angle is the most important variable that affects the angle after the surgery. Finally, in conclusion, this study the SARPE surgery changes significantly the PP-SN angle. The PP-SN angle after SARPE surgery depends on the PP-SN angle before the surgery.

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## 1. Introduction

In a normal condition, the upper jaw (maxillary arc) should be wider than the lower jaw (mandibular arch). However, it is not the case for some people who have a smaller upper jaw than lower jaw. Due to this condition, these people might have some problems such as difficulties in chewing, talking, and other issues. This is why it is important to correct the upper jaw.

Orthodontists try to correct this condition by making wider the maxillary arc. The non-surgical rapid palatal procedure has been used routinely in children to widen the maxilla and correct transverse discrepancies between the upper jaw and lower jaw. The rationale is that the orthopaedic force exerted from the expander can open the mid-palatal suture, which is usually patent in young children, and thus the maxilla is expanded (Haas, 1970). In adults or skeletally mature adolescents where the mid-palatal suture has fused the non-surgical rapid palatal procedure is not commonly used due to several drawbacks (Alpern and Yurosko, 1987).

Nowadays, surgically assisted rapid palatal expansion (SARPE) has become a popular treatment for adults. SARPE is a form of surgery in which the upper jaw is expanded. In this study, the palatal plates of the patients who have a small upper jaw were expanded to become normal. They used an appliance as displayed in Figure 1 below.



Figure 1. Illustration of a palatal expansion device that is used in this study.

It is expected that the SARPE will result to a better condition for the patients' head structure. Figure 2 displays the jaw structure before SARPE (solid line) and the expected structure after SARPE (dashed line) is performed.

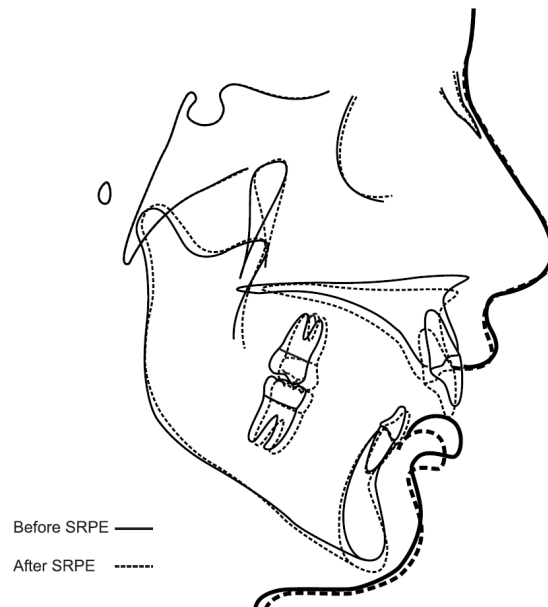


Figure 2. The image profile (cephalogram) of patients before SARPE and after SARPE.

The objective of this study are to analyze the changes in the X-Ray image profile (cephalogram) of patients before and after the SARPE surgery and to investigate whether it is possible to predict the Palatal Plane-Sella Nasion Plane (PP-SN) angles after surgery based on patients characteristics using parametric and non parametric regression methods.

To address the objectives, exploratory data analysis (EDA), t-paired test, regression analysis, regression tree and random forest were performed.

The structure of this thesis is as follows. The dataset is described in section 2. The statistical methods used and the results will be presented in section 3 and 4, respectively. Discussion and concluding remarks will be given in section 5.

## 2. Data

The dataset contains over 50 patients who underwent a surgically assisted rapid palatal expansion (SARPE) in which eight angles (cephalometrics measurement) for each patient were measured before and after jaw surgery in order to determine the impact of the surgery. The definition for eight cephalometrics measurements are shown in Table 1 and Figure 3.

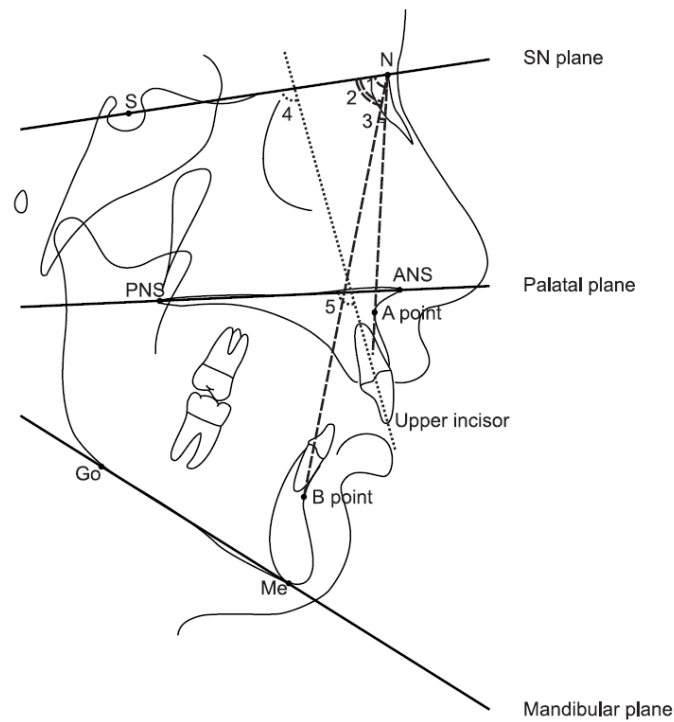


Figure 3. Cephalometrics measurements: SNA, SNB, ANB, U1-SN, U1-PP, PP-SN, PP-Man and SN-Man, in degrees.

Table 1. Definition of the cephalometric measurements

Angle( $^{\circ}$ )	Definition
1. SNA	Sella Nasion A-point (Maxillary prominence)
2. SNB	Sella nasion B-point (Mandibular prominence)
3. ANB	Skeletal AP relationship
4. U1-SN	Upper Incisor-Sella Nasion Plane
5. UI-PP	Upper Incisor-Palatal Plane
<b>6. PP-SN</b>	<b>Palatal Plane- Sella Nasion Plane</b>
7. PP-Man	Palatal Plane-Mandibular Plane
8. SN-Man	Sella Nation- Mandibular plane

In this paper, the main interest of the researcher is the **Palatal Plane-Sella Nasion Plane (PP-SN)** angle because this angle was affected directly by the surgery. For the first objective,

we focus on the PP-SN angle changes before and after surgery. The response variable for regression analysis is the PP-SN post jaw surgery and the covariates are PP-SN pre surgery, age, gender and occlusion (occlusion type II and occlusion type III). Occlusion is the way that the upper and lower rows of teeth line up in the human mouth. There are three classes of occlusion meaning that there are three different ways that teeth line up in the mouth as displayed in Figure 4. Class I occlusion is what is typically considered as the ideal or normal condition (balance between the upper and lower jaws). Class II occlusion, the bottom jaw sits slightly behind where it should. It is sometimes lead to a functional problem. Class III occlusion creates the opposite problem to Class II occlusion. In this case, the top jaw is further back than it should be. Functionally, a person with a severe Class III occlusion might have difficulty biting.

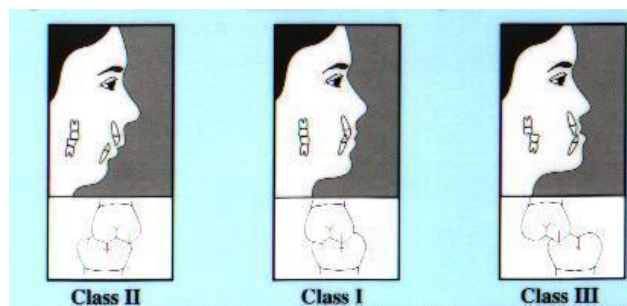


Figure 4. Three classes of occlusion (Spiller, 2000).

### 3. Statistical Methods

#### 3.1 Exploratory Data Analysis (EDA)

Firstly, in order to get the idea about the pattern of the data, the exploratory data analysis (EDA) was performed. Descriptive statistics including the means, the standard deviations for each measurement for each angle were calculated. Several graphical results were also displayed.

#### 3.2 Student's t-paired test

To address the first objective the Student's paired *t*-test was carried out. The PP-SN angle before (pre) and after (post) the surgery was compared. The paired *t*-test provides a hypothesis test of the difference between population means for a pair of random samples whose differences are approximately normally distributed (Armitage and Berry, 1994).

### 3.3 Regression Analysis

The second aim, to predict the PP-SN angle after surgery based on patients' characteristics, is addressed by using a regression analysis. Regression is a technique used to find the best linear prediction of a criterion variable from a set of predictor variables. A first order linear multiple regression function of the form given below was employed.

$$Y_i = \beta_0 + \beta_1 X_{i1} + \dots + \beta_{p-1} X_{i,p-1} + \varepsilon_i$$

In the model proposed above  $Y_i$ , is the response (in this case is PP-SN post surgery) of patient  $i$ ,  $\beta_0, \beta_1, \dots, \beta_{p-1}$  are parameters, and  $X_1, X_2, \dots, X_{p-1}$  are predictor variables which in this study are PP-SN pre surgery, age, gender (1=Male and 0= Female), occlusion ( 1=Class II and 0= Class III), and any interactions between the predictors.

After the saturated model (the model that includes all the possible explanatory variables) is fitted we performed a model selection procedure to determine a 'good' subset of covariates which influence PP-SN post surgery. The selection of a good subset of covariates is based on the next criteria: R-Square, Adjusted R-Square, Mallows  $C_p$  criteria, and Akaike information criteria (AIC). Similarly, we seek for subsets of the predictors with larger Adjusted R-Square value; small  $C_p$  values close to  $p$  (number of parameters); and the smallest AIC value.

For the reduced model, we need to examine the assumption of the model before making inferences based on the model. The model assumptions are:

1. Regression function is linear. Whether a linear regression function is appropriate for the data being analyzed can be studied from a residual plot against the predictor variable or from a residual plot against the fitted values. If there is no pattern, this means that the model is linear.
2. The error terms is normally distributed. The QQ-plot shows if there is normality. A linear shape of this plot means that the model is normal.
3. The error terms have constant variance (Homoscedasticity). Testing the constancy of the variances of the error terms can be done using the Breusch-Pagan test. The null hypothesis of this test says that the variances of the error terms are constant. The decision rule follows that if  $\chi_{BP}^2 < \chi_q^2$  at the 5% level of significance, then we fail to reject the  $H_0$  and conclude that there is equal variance in the data. Otherwise, we reject the  $H_0$  and conclude that there is unequal variance in the data.



4. The error terms are independent and test multicollinearity using variance inflation factor (VIF) value, if  $VIF > 10$  means there is a multicollinearity.

We also tried to detect whether there are outliers and influential observations by the following statistics:

1. Studentized deleted residuals. It is used for identifying the outlying in response  $Y$ .
2. Leverage Values (Hat Diag). It is a measure of how far an observation is from the others in terms of the levels of the independent variables (not the dependent variable). Observations with values larger than  $h_{ii} > \frac{2p}{n}$  are considered as outliers, where  $p$  is the number of parameter and  $n$  is the sample size.
3. DFFITS. It is used to measure of how much an observation has effected its fitted value from the regression model. Values larger than  $2 * \sqrt{\frac{p}{n}}$  in absolute value are considered highly influential.
4. DFBETAS. It indicates whether inclusion of a case leads to an increase or a decrease in the estimated regression coefficient, and its absolute magnitude shows the size of the difference relative to the estimated standard deviation of the regression coefficient. Values larger than  $\frac{2}{\sqrt{n}}$  in absolute value are considered as an influential case (Neter, *et al.* 2005).

### **3.4 Regression Tree and Random Forests**

The nature of the relationship between the predictors and the response may not be necessarily linear. The next step in order to account for an inherent unknown relationship, a method that can capture non-linear associations is considered. We carried out the regression trees (Breiman *et al.* 1984) in order to get an understanding of what variables or interactions of variables that related to the response in this case is PPSN angle post surgery. To obtain the variable importance the random forests methods (Breiman, 2001) was performed. All four variables were used in the analysis for the prediction of the PPSN angle post surgery. The characteristics of the patients were included as characteristics patient's variables.

### 3.4.1 Regression Tree

The regression tree approach is a widely used technique to model the relationship between a response and predictors without prior knowledge of the relationship between them. This method is used for constructing a set of a decision rules on the predictor variables recursively partitioning the data into successively smaller groups with binary splits based on a single predictor. The optimum split is selected based on a split that maximizes the heterogeneity of the two resulting groups with respect to the response variable. The regression tree approach starts by building a maxima tree and based on cross-validation, the tree is pruned to an optimum size to avoid over fitting. The regression tree analysis was performed using *tree*, and *rpart* packages in R 2.11.

### 3.4.2 Random Forests

Random forests (Breiman, 2001) is among the newest and most promising developments in extracting the variables' importance ranking. In random forests, one grows a number of trees by bootstrapping the sample (i.e., randomly selecting  $n$  observations from the original data with replacement) and searching over only a randomly selected subset of inputs at each split. The results from these trees are then integrated.

In order to select the variables, there are two variable important measures provided in the Random Forest package in R:

1. Mean Decrease Accuracy (*%IncMSE*): It is the average increase in squared residuals of the test set when the variable is permuted. A higher *%IncMSE* value represents a higher variable importance.
2. Mean Decrease Gini (*IncNodePurity*): Measures the quality (NodePurity) of a split for every variable (node) of a tree by means of the Gini Index. A higher *IncNodePurity* value represents a higher variable importance, i.e. nodes are much 'purer' (Kuhn, *et al.*, 2008).

Strobl *et al.* 2007 shows that the *IncNodePurity* is biased, hence we use Mean Decrease Accuracy (*%IncMSE*) to see the variable importance.

## 4. Result

### 4.1 Exploratory Data Analysis (EDA)

Firstly, we observe the direction of the angle change (differences of PP-SN angle before and after surgery). Table 4.1 shows that more than half of the patients (e.g., 58%) have a higher angle of PP-SN after surgery than before the surgery. However, some patients have a lower PP-SN angle (22%). The similar percentage occurs for the patients who show no different of the PP-SN angle before and after the surgery.

Table 4.1. The number of patients who has positive, negative or not difference change of angles before and after the surgery.

<i>Angle(°)</i>	<i>Direction of change</i>		
	<i>Increase(+)</i>	<i>Decrease(-)</i>	<i>No change(different=0)</i>
<b>PP-SN</b>	29	11	10

Then we explored further the PP-SN angle as shown in Table 4.2 where the minimum, maximum, mean and standard deviation value of angle PP-SN by gender are presented.

Table 4.2. The descriptive statistics of angle PP-SN by gender

<b>Gender</b>		<b>N</b>	<b>Minimum</b>	<b>Maximum</b>	<b>Mean</b>	<b>Std. Deviation</b>
Female	PP-SN(pre)	30	-1	15	5.20	3.458
	PP-SN(post)	30	0	16	5.77	3.839
Male	PP-SN(pre)	20	1	15	6.25	3.945
	PP-SN(post)	20	1	16	7.75	3.740

From Table 4.2, we observe that on average after the surgery the male patients tend to have a higher value (or increase) of PP-SN angle whereas for female patients only a slight increase. This is can be seen also in the boxplot shown in Figure 4.1. Three patients have high value than the other.

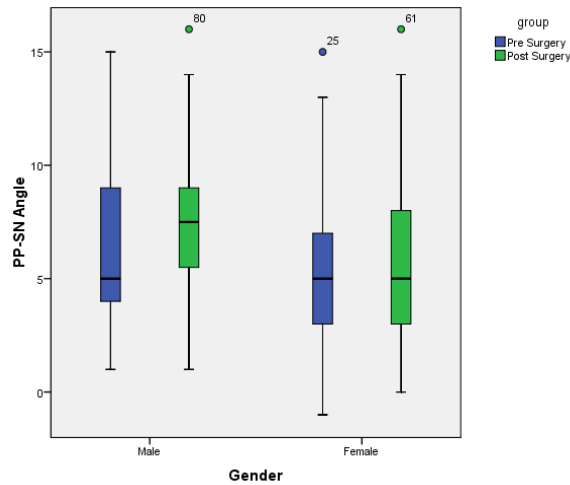


Figure 4.1. Boxplot for angle PP-SN pre surgery and post surgery by gender.

Occlusion is also a factor that is interesting to be explored. The descriptive statistics for PP-SN by occlusion can be seen in Table 4.3. We can see that in average patients in occlusion class II seems to have lower value than patients in Class III. It clearly can be seen in the box plot presented in Figure 4.2.

Table 4.3. The descriptive statistic of angle PP-SN by occlusion.

Occlusion		N	Minimum	Maximum	Mean	Std. Deviation
Class III	PP-SN(pre)	15	1	15	6.67	4.100
	PP-SN(post)	15	1	16	7.13	3.662
Class II	PP-SN(pre)	35	-1	13	5.17	3.417
	PP-SN(post)	35	0	16	6.31	4.006

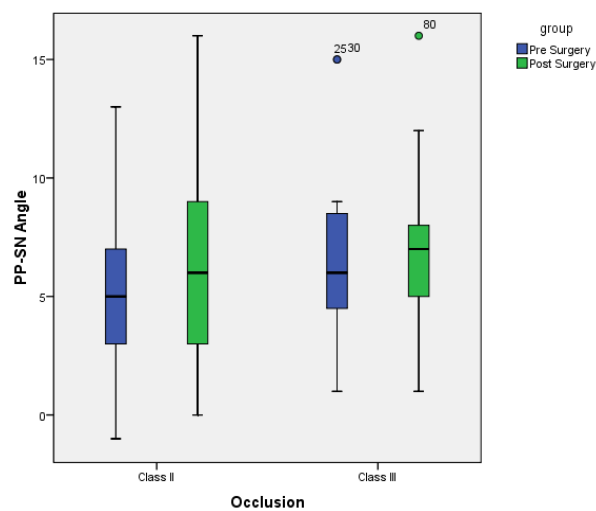


Figure 4.2. Boxplot for angle PP-SN pre surgery and post surgery by occlusion.

Another factor to be explored is the age of the patients. The range age of the patients is from 16-50 years old. Most of the patients are 20 - 30 years old. The distribution of the age can be observed in the histogram presented in Figure 4.3.

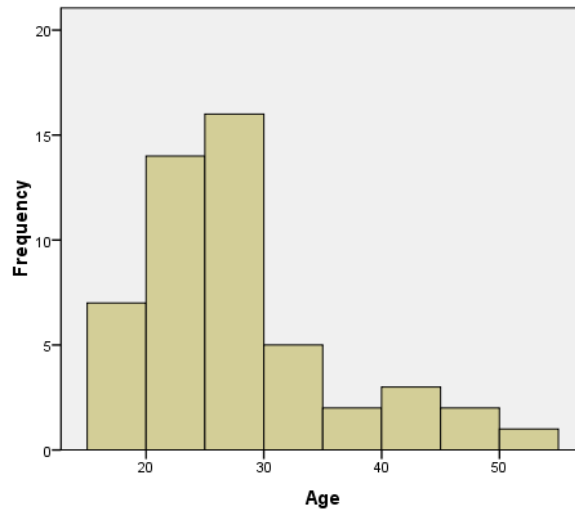


Figure 4.3. The histogram of age distribution.

Next, we explored the relationship between age and PP-SN angle by a scatter plot presented in Figure 4.4. From the scatter plot, it seems there is no relationship between Age to PP-SN angle post surgery.

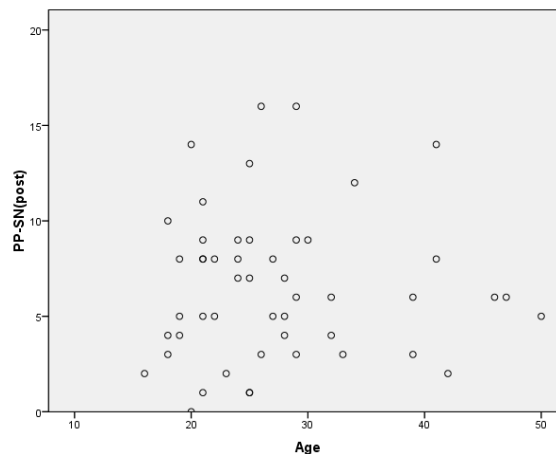


Figure 4.4. Scatter plot between age and PP-SN post surgery.

The relationship between PP-SNpre and PP-SNpost surgery can be explored using a scatter diagram in Figure 4.5. The scatter diagram showed a clear relationship between PP-SN pre and PP-SN post. Patients who have lower PP-SN pre tend to have also lower of PP-SN post. The higher value of PP-SN pre, the higher the angle of PP-SN post surgery.

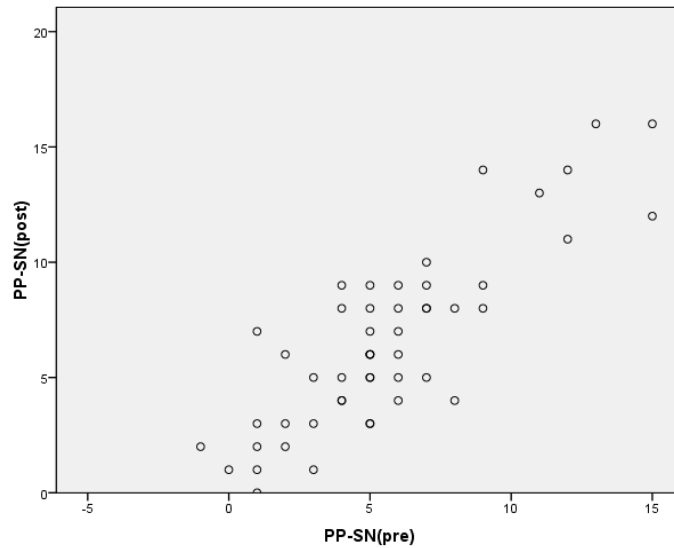


Figure 4.5. A scatter diagram showing the relationship between PP-SN pre and PP-SN post

## 4.2 Paired *t*-test

Now we analyze the changes of PP-SN Pre and Post Surgery by using paired *t*-test. Table 4.4 displays the summary for angle PP-SN in both measurements and the paired *t*-test result for the angle PP-SN change. Overall the PP-SN angle statistically significantly increase after the surgery by around 1°.

Table 4.4. The *t*-paired test statistics result

Angle(°)	<i>Pre surgery</i>		<i>Post surgery</i>		<i>Changes</i>		<i>95% CI Changes</i>		<i>Prob.</i>
	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>Lower</i>	<i>Upper</i>	
<b>PP-SN</b>	5.62	3.66	6.56	3.89	0.94	2.13	0.33	1.55	0.003

## 4.3 Regression Analysis

Regression analysis was performed to investigate whether it is possible to predict the angles after surgery based on patient's characteristics. The angle PP-SN is the interest of this analysis. First, we tried to include all covariate and their possible interactions to find the best model, finally we got three possible models (Table A1 in appendix). Model 1 only considers variable PP-SN pre. Model 2 considers interaction between age and gender and interaction between age and occlusion, but if we included the main effect together with the interactions in this model, only variable PP-SN pre was significant. Model 3 includes all characteristic patients without interaction between independent variable. Finally, based on the R square, Adjusted R square, Cp, and AIC, we choose model 3 and obtained the following model:

$$\hat{y} = -1.331 + 0.897 \text{ PPSNpre} + 1.483 \text{ Gender} + 0.063 \text{ Age} + 0.768 \text{ Occlusion}$$

The significances for the each regression parameter are presented in Table 4.5. The angle PP-SN pre surgery has a significant effect on the PP-SN angle post surgery at level of significance 5%. It means that a unit increase PP-SN pre surgery would lead to an increase the angle of post surgery by 0.897 when the other variable held constant. We also see that the gender results different PP-SN angle. Male tends to have higher angle of post surgery compare to female patients. It can be seen already in the EDA part (see Figure 4.1). Age and occlusion have not significant effect to the PP-SN post surgery.

Table 4.5. The coefficients regression and their significances for model angle PP-SN post surgery.

Variable	Coefficients		t	P-value	VIF
	Parameter estimate	Standard Error			
(Constant)	-1.331	1.296	-1.027	0.310	
PPSN(pre)	0.897	0.081	11.133	0.000	1.049
Gender	1.483	0.619	2.396	0.021	1.133
Age	0.063	0.036	1.740	0.089	1.073
Occlusion	0.768	0.656	1.170	0.248	1.115

Coefficient determination for this model is 0.753, it means that 75.3 % of the total variance in Y (angle PP-SN post surgery) can be explained by PP-SN pre, gender, age and occlusion. The other 24.7% of the total variation value in angle PP-SN post surgery remained unexplained.

We then performed diagnostic of analysis regression:

### 1. **Linearity**

A residual plot is made to check if a linear model is appropriate. The residual plot displayed in Figure 4.6 showed that there is no pattern. This means that the linear regression function is appropriate.

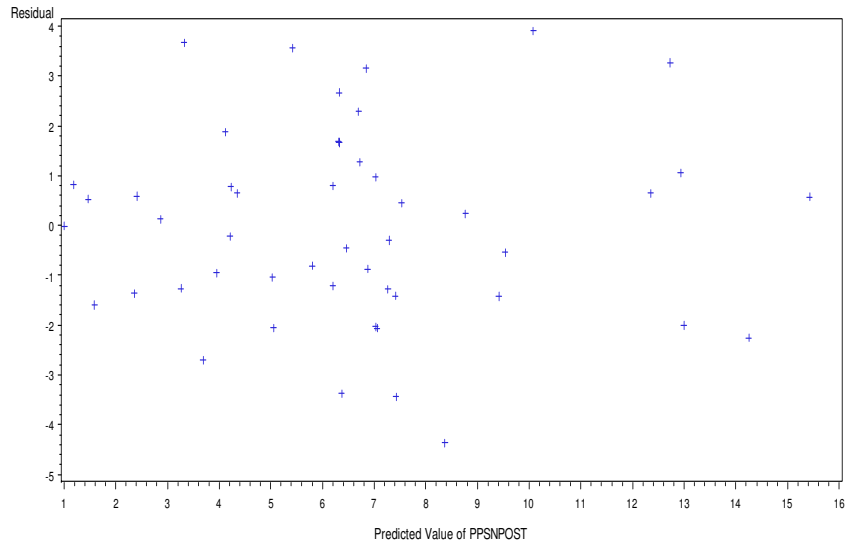


Figure 4.6. Residual Plot against the fitted value

## 2. Normality

The QQ-plot shown in Figure 4.7 shows reasonably close to a straight line, suggesting that the distribution of the error terms does not depart substantially from a normal distribution.

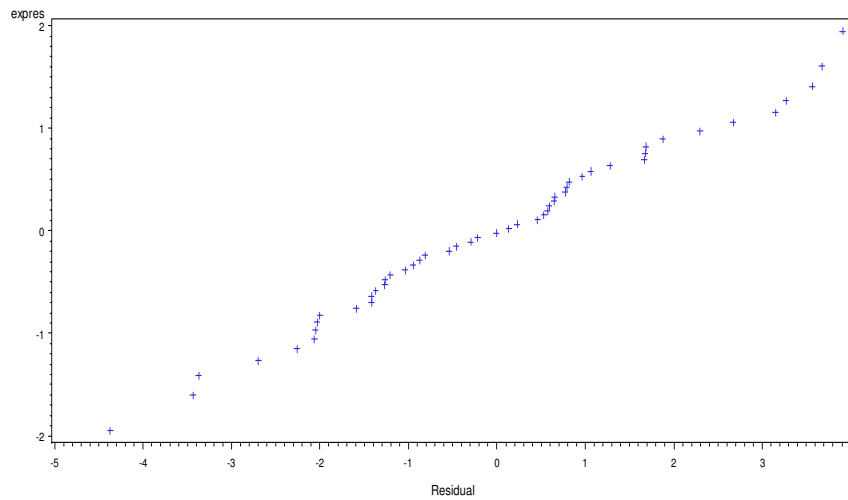


Figure 4.7. QQ plot for normality

The coefficient of correlation between ordered residuals and expected values under normality for the estimated mode is  $0.99422 >$  the critical value ( $0.977$ ) for indicates normality.



### 3. Homoscedasticity (Breusch Pagan Test)

The residual plot in Figure 4.6 is also helpful to examine if the variance of the error term is constant. The plot suggests that a constant variance. Furthermore we can use formal test for testing the constancy of the variances of the error terms using the Breusch-Pagan test. The null hypothesis of this test says that the variances of the error terms are constant. The null hypothesis will be accept if the  $\chi^2_{BP}$  follows approximately the chi-square distribution with one degree of freedom. The  $p$ -value obtained is 0.4688. This means that the variances of the error terms are constant.

4. **Multicollinearity:** Here there is no problem with multicollinearity (Table 4.6) since all the VIF values are below 10.

### 5. Detecting outlier and influential observations.

First, we identified outlier on Y and X observations. Based on the Table A2 in the appendix, we can see no outlier found in Y and there is one observation is as outlier in X, subject number 25. The next step is to check whether or not this outlier is influential. We used DFFITS and DFBETAS to measure the influence. According to these measurements, this outlier is an influential outlier. Then we tried to fit the model again by excluding the influential outlier. The differences in the estimates of the parameters are presented in Table A3 in the appendix. There are not much different results if we take the influential observation out. The parameter estimates when the outlier is taken out, are more or less the same. The adjusted R-square for model built with and without outlier are 0.753 and 0.730, respectively.

## 4.4 Regression Tree

In the regression tree, we start with the maximum tree which includes all variables. The most complex tree is presented in Figure 4.8. There are 12 terminal nodes (or leaves) produced from 11 splits. In each, the means of the PP-SN angle post surgery and number of samples in each node are displayed as well. The tree indicates that PP-SN angle post surgery has a non-linear function with the angle before surgery.

## PPSNpost

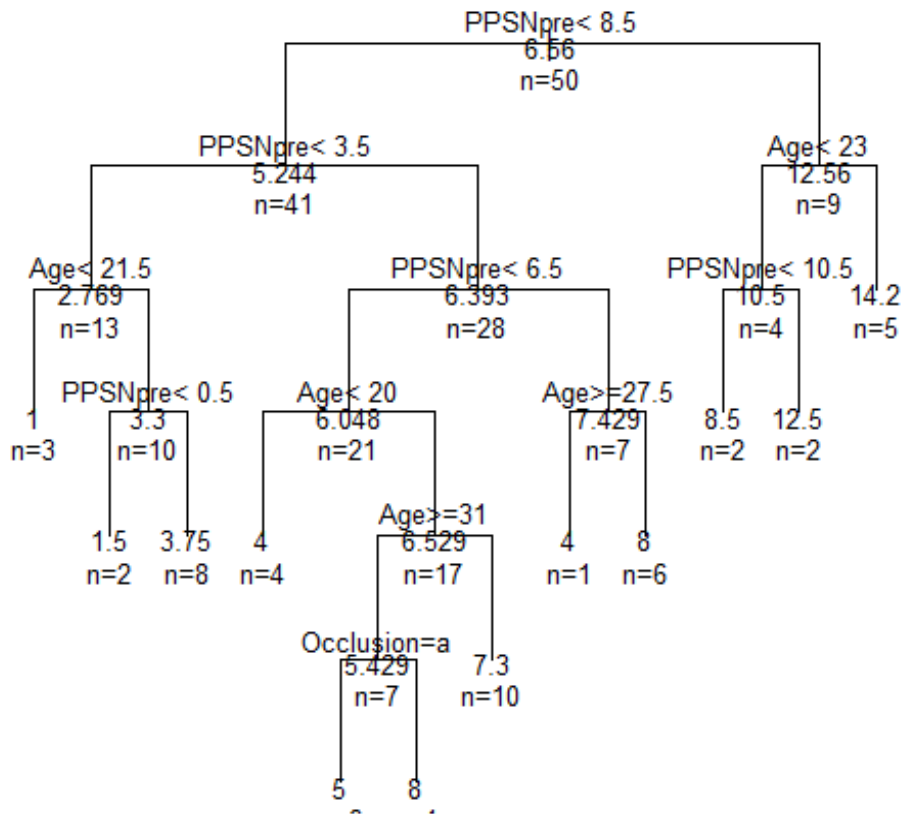


Figure 4.8. A fully grown tree for PP-SN angle post surgery.

From the tree in Figure 4.8, we observe that the overall PPSN post is  $6.56^\circ$  (in the root level). For the patients with the PPSN angle before surgery larger than  $8.5^\circ$  (9 patients), the average angle after surgery equals  $12.56^\circ$ . The average of PPSN post for the rest of patients (with PPSN pre  $< 8.5^\circ$ ) equals  $5.24^\circ$ .

In the other hand, patients with the PP-SN angle before surgery less than  $3.5^\circ$  (13 patients), the average angle after surgery are  $2.77^\circ$ . Meanwhile, age factor have effect on the patients (28 patients) with angle before surgery between  $3.5^\circ$  and  $8.5^\circ$ .

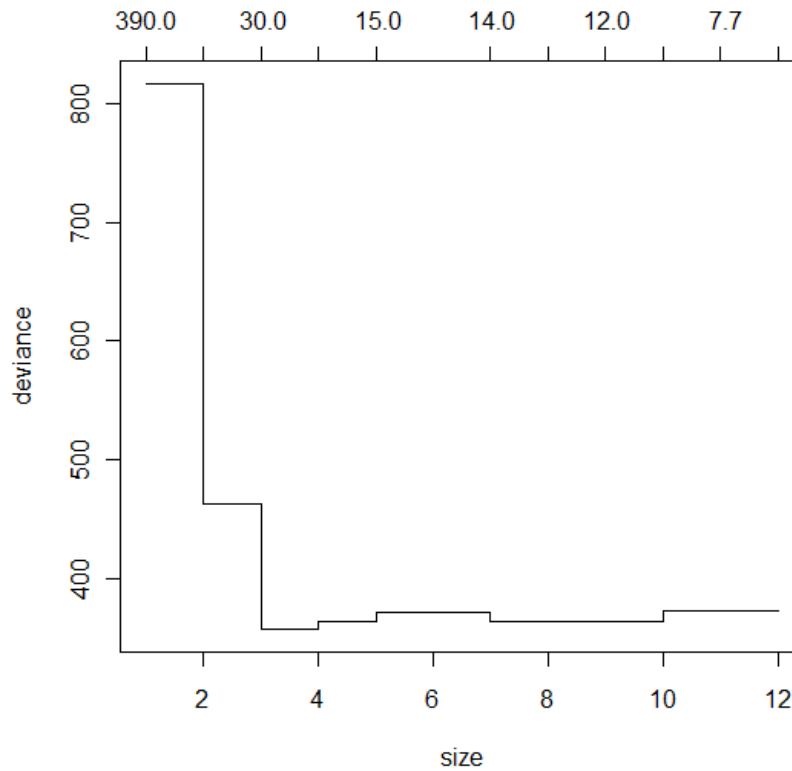


Figure 4.9. The deviance versus the size of number terminal nodes from Random Forests.

The next step is the pruning procedure based on cross-validation to snip off the least important splits. The K-fold cross-validation is performed to find the deviance. Figure 4.9 show the obtained deviance versus number of terminal nodes. The tree model with only a single terminal node (no split) results a deviance value 817. Splitting it into two terminal nodes decreases the deviance equals to 462. The minimum deviance is obtained for the tree with only 3 terminal nodes (deviance=356). The plot of this tree is presented in Figure 4.10. The pruned tree only includes the PP-SN pre surgery as the predictor. The predicted regression lines for the three groups are presented in Figure 4.11. We observe a step regression line here.

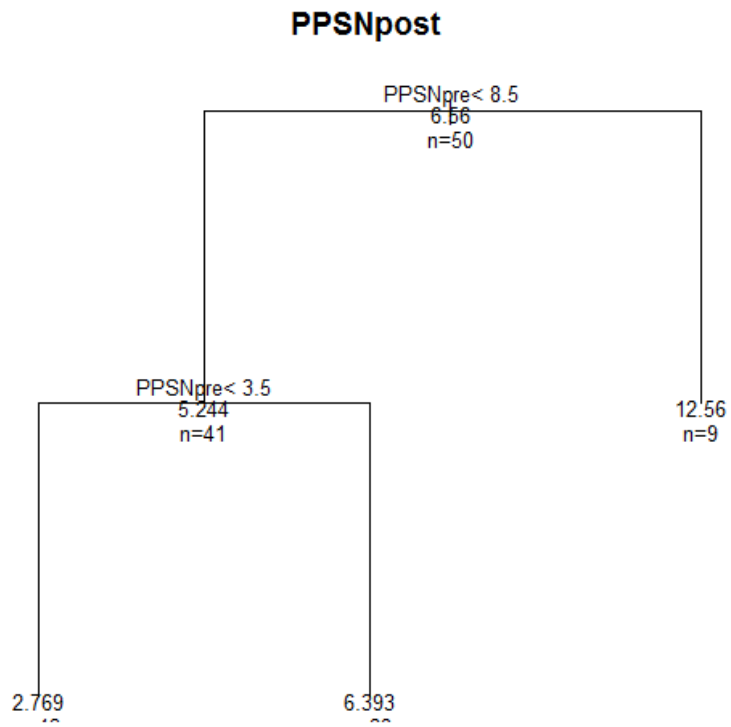


Figure 4.10. The pruned tree model for PP-SN post variable using 3 terminal nodes.

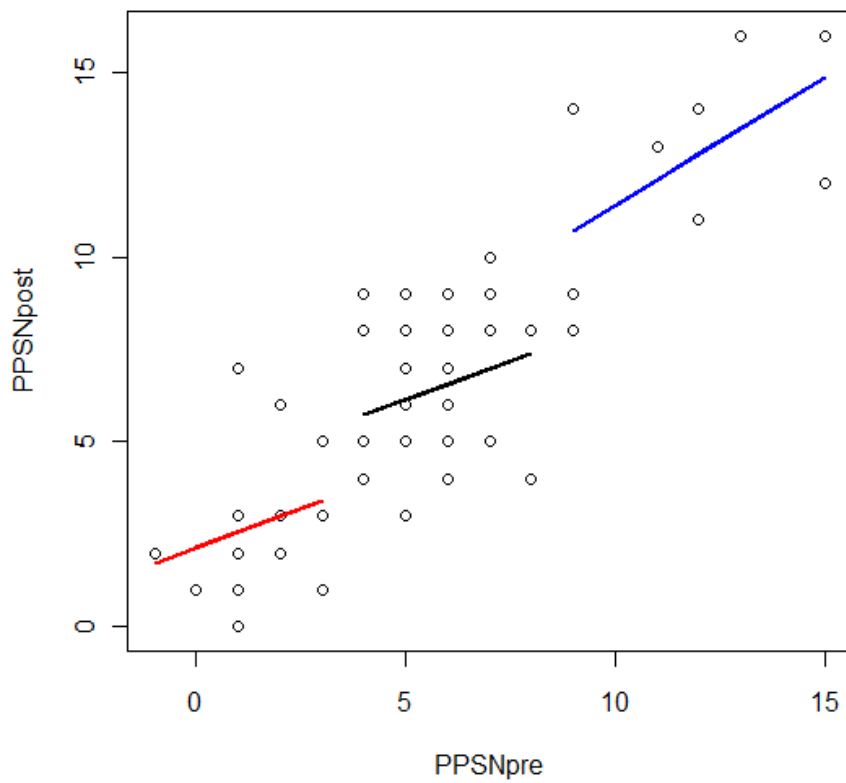


Figure 4.11. The regression lines in the tree classes.

## 4.5 Random Forest

In order to obtain variable importance, the random forest method was carried out. In this step 10,000 trees were grown. A histogram of number of terminal nodes (tree size) from the 10,000 trees is presented in Figure 4.12. Number of terminal nodes varies from 1 to 20 terminal nodes. Nevertheless, most of the grown trees have terminal nodes from 4 to 11 nodes.

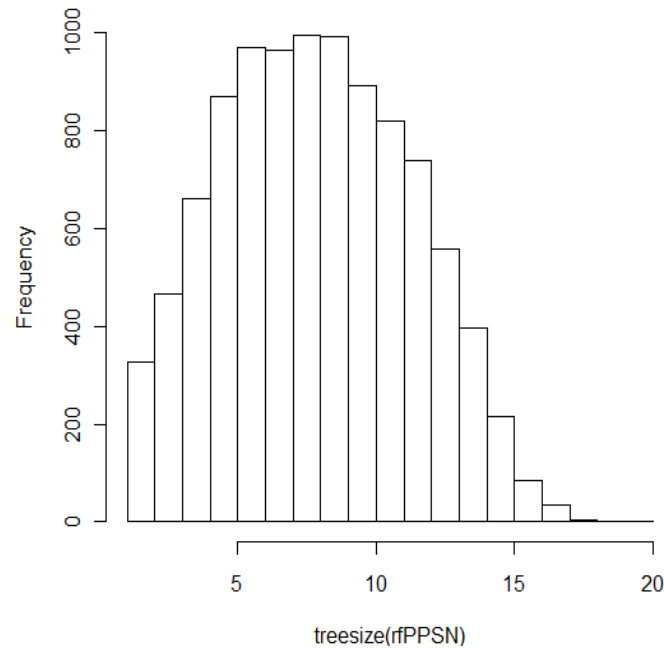


Figure 4.12. Histogram of the number of terminal nodes (treesize) from 10,000 trees.

The results for variable importance measure %IncMSE which are provided by the *RandomForest* package is presented in Table 4.7 and Figure 4.13.

Table 4.7. The ranked variable importance is measured by the increased in percentage of mean square error (%IncMSE) in RF

Variables	%IncMSE
PPSNpre	8.32
Gender	0.22
Occlusion	-0.30
Age	-0.74

From Table 4.7 and Figure 4.13 we can observe that the PP-SN pre surgery is the most important variable. The importance of PP-SN pre surgery is much larger than the other predictors' importance which only have Mean Decrease Accuracy (%IncMSE) close to zero. This fact can be seen clearly in the tree diagram displayed in Figure 4.8 where the PP-SN pre surgery defines most of the splits in the tree. The second largest %IncMSE is Gender, followed by Occlusion and Age which both have negative values.

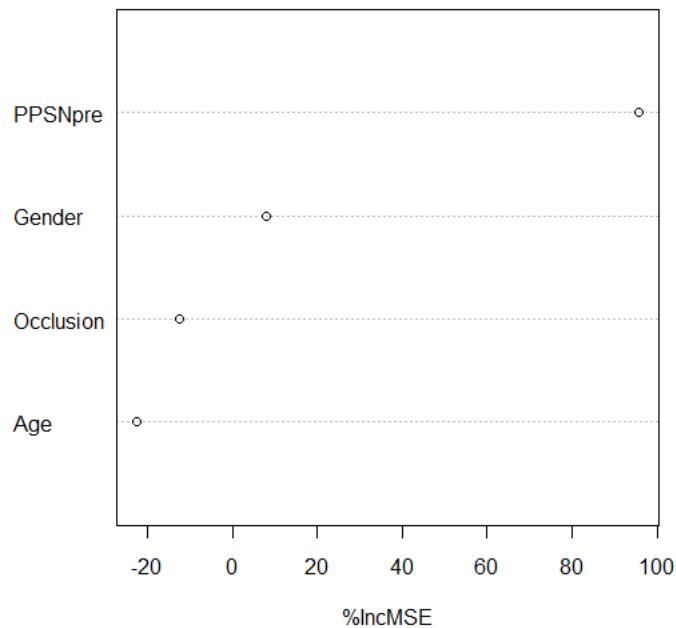


Figure 4.13. Mean Decrease Accuracy (%IncMSE) for PP-SN post variable.

## 5. Discussion and Conclusion

SARPE is a widely used procedure for the correction of upper jaw or maxillary. This study investigated the changes of PP-SN angle of patients before and after the SARPE surgery, and investigated possibility to predict the angles after surgery based on patients characteristics.

The exploratory data analysis showed that more than half of the patients (e.g., 58%) have a higher PP-SN angle post/after surgery than before. It means that most of the patients which have narrow maxillary were overall significantly increase after surgery. We can observe from the result of *t*-paired test that the changes was significantly different between angle PP-SN pre surgery dan PP-SN post surgery, this is an indication that most of the patients after SARPE have wider PP-SN angle.

Further, to investigate the effect of other patients' characteristics (PP-SN pre surgery, age, gender and occlusion type) on the PP-SN post surgery, two approaches were performed, using parametric regression and non-parametric regression (regression tree and random forests).

In analysis regression, we tried to find the best model by using selection model procedure and came up with a final model that includes all the characteristics patients. It is shown that variable PP-SN pre surgery and Gender were statistically significant at  $\alpha = 5\%$ .

There is no violation of assumptions of analysis regression, but there is one possible influential observation that had been investigated. There is not much different in the parameter estimates in the model if we include or exclude the influential outlier. Hence we keep the observation. However, we reported this outlier and gave a recommendation to the researcher to explore more to this patient in further research.

In the non-parametric approach, regression tree showed that the PP-SN pre surgery has an effect on the PP-SN post surgery. There are three classes based on different cut-off from PP-SN pre surgery. This result is in line with the finding in the random forest where PP-SN pre is much more important than the other predictor variables. Based on the variable importance from random forests, the PP-SN pre surgery is the most important variable that contributes to the PP-SN post surgery. Variable Gender is in the second position, but the value of *%incMSE* is small and rather close to zero. This means that variable Gender is less important. Variable Age and Occlusion have negative value of *%IncMSE* indicating that variable is completely uncorrelated with the response.

In this study the analysis regression, regression tree and random forest provide similar results that the PP-SN pre surgery angle is the most important variable that affects the PP-SN angle after SARPE surgery. Nevertheless, in the linear regression analysis, Gender has a significant effect although much smaller compared to PP-SN pre surgery. The results from both approaches (linear regression and regression trees) were not exactly giving the same results. It can be understood, since the way to fit the model is different. In regression analysis, we tried to fit a global model, in other hand in the regression tree we fitted model locally, by making partitions in data set.

Finally, in conclusion, in this study the SARPE procedure changes significantly the PP-SN angle. The PP-SN angle after SARPE procedure depends on the angle before the surgery and gender of the patients.

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## Appendix

Tabel A1. The model selection for analysis regression by including all possible interactions

<b>Model</b>	<b>R-Square</b>	<b>Adjusted R-Square</b>	<b>C(p)</b>	<b>AIC</b>	<b>Variables in Model</b>
1	0.7089	0.7028	5.6808	77.0540	PP-SNpre
2	0.7597	0.7440	0.6546	71.4564	PP-SNpre agegender ageocclusion
3	0.7533	0.7314	5.0000	74.7687	PP-SNpre age gender occlusion

Table A2. Test for outlier and influential outlier. Studentized deleted residual, Leverage, DFFITS and DFBETAS values.

Obs	Residual	Studentized deleted residual	Leverage	DFFITS	DFBETAS				
					Intercept	PPSNPre	AGE	gender	occlusion
1	-2.698	-1.388	0.05	-0.318	-0.17	0.1151	0.1151	0.1434	-0.083
2	-1.414	-0.73	0.0835	-0.22	0.1012	0.0171	-0.084	-0.171	-0.097
3	-4.371	-2.337	0.0527	-0.551	0.0147	-0.291	0.0456	0.2574	-0.202
4	1.8791	1.0047	0.1378	0.4017	-0.171	-0.114	0.3183	-0.023	0.0181
5	1.2769	0.6563	0.0792	0.1924	0.0147	-0.021	-0.06	0.1267	0.0996
6	-0.218	-0.111	0.0737	-0.031	-0.022	0.0052	0.0216	0.0145	-0.009
7	1.6745	0.8493	0.048	0.1908	0.0726	0.0335	-0.082	-0.1	0.0683
8	0.2319	0.1183	0.0737	0.0334	-0.008	0.0065	-0.002	0.0237	0.0186
9	-1.59	-0.826	0.0924	-0.264	-0.193	0.1424	0.1505	0.0969	-0.047
10	-0.458	-0.237	0.0946	-0.077	-0.008	0.0186	-0.022	-0.035	0.0481
11	3.2712	1.7973	0.1433	0.735	-0.12	0.621	-0.091	-0.256	0.2295
12	3.5713	1.8649	0.0466	0.4121	0.1912	-0.003	-0.182	-0.212	0.1381
13	0.7754	0.4037	0.1078	0.1403	0.0702	-0.068	-0.018	0.0527	-0.083
14	1.6712	0.8768	0.1094	0.3074	0.2027	0.0249	-0.091	-0.184	-0.221
15	-3.371	-1.774	0.0675	-0.477	0.2025	-0.017	-0.319	0.105	-0.086
16	1.0621	0.5654	0.1436	0.2315	-0.05	0.1521	-0.058	0.0962	0.1164
17	3.1547	1.6685	0.0842	0.5058	0.263	0.1293	-0.349	-0.244	0.1652
18	-1.203	-0.617	0.0756	-0.176	0.0295	0.0423	-0.012	-0.135	-0.083
19	-0.809	-0.419	0.0991	-0.139	-0.067	0.0039	-0.004	0.0763	0.1122
20	0.5929	0.3014	0.0658	0.08	0.0127	-0.048	0.0185	-0.02	0.0101
21	2.6709	1.3954	0.0782	0.4064	-0.108	-0.094	0.079	0.3161	0.1831
22	-1.035	-0.52	0.041	-0.108	-0.003	0.019	-0.025	0.0419	-0.028

Obs	Residual	Studentized	Leverage	DFFITS	DFBETAS				
		Deleted Residual			Intercept	PPSNPre	AGE	gender	occlusion
23	0.6447	0.337	0.1161	0.1222	-0.048	0.0762	-0.002	0.0641	0.063
24	-1.417	-0.736	0.0951	-0.239	-0.082	-0.06	0.0668	-0.071	0.1176
25	-2.257	-1.294	<b>0.2388</b>	<b>-0.725</b>	0.1242	<b>-0.527</b>	-0.194	0.2702	<b>0.3097</b>
26	0.9662	0.492	0.0655	0.1303	0.0554	0.0388	-0.074	-0.066	0.0456
27	-0.874	-0.463	0.1379	-0.185	0.111	-0.008	-0.158	0.0141	-0.017
28	-2.001	-1.073	0.1405	-0.434	0.1105	-0.289	0.0884	-0.186	-0.219
29	0.4601	0.2388	0.104	0.0814	0.0331	0.0178	-0.002	-0.046	-0.061
30	0.5739	0.3143	0.1948	0.1546	-0.047	0.1139	0.0359	0.0375	-0.046
31	3.9157	2.1412	0.1103	0.7538	-0.466	0.3873	0.4897	-0.145	0.1549
32	-0.543	-0.279	0.0902	-0.088	-0.023	-0.023	0.0148	-0.029	0.0456
33	-3.431	-1.832	0.0905	-0.578	-0.09	-0.015	0.2685	-0.328	-0.301
34	-0.008	-0.004	0.0838	-0.001	-7E-04	0.0008	0.0003	0.0004	-2E-04
35	-0.949	-0.478	0.0435	-0.102	-0.031	0.0381	0.0044	0.0421	-0.025
36	0.136	0.0687	0.0554	0.0166	0.0086	-0.009	-0.005	-0.007	0.0036
37	0.5322	0.2875	0.173	0.1315	0.122	-0.056	-0.067	-0.064	-0.082
38	0.6533	0.3433	0.1253	0.1299	0.1078	-0.02	-0.057	-0.074	-0.09
39	0.8209	0.4357	0.1412	0.1767	-0.025	-0.108	0.1023	-0.012	0.0023
40	-2.052	-1.063	0.0787	-0.311	-0.204	0.0065	0.2249	0.1471	-0.091
41	-2.034	-1.046	0.0655	-0.277	-0.118	-0.083	0.158	0.1395	-0.097
42	-2.063	-1.131	0.1749	-0.521	0.3292	-0.021	-0.462	0.0217	-0.035
43	0.7933	0.4084	0.0874	0.1264	0.0379	-0.033	0.0064	0.0544	-0.08
44	1.6846	0.9249	0.1851	0.4408	-0.122	-0.109	0.3076	0.193	-0.226
45	-1.262	-0.659	0.109	-0.231	-0.042	0.1319	0.0406	-0.144	-0.082

46	-1.368	-0.729	0.1417	-0.296	-0.167	0.1892	0.0498	-0.1	0.1612
47	3.6755	1.9938	0.1072	0.6909	0.0975	-0.397	-0.085	0.4429	0.2447
48	2.2974	1.1683	0.0394	0.2366	-9E-04	0.051	0.0163	-0.111	0.0815
49	-0.292	-0.15	0.0874	-0.047	-0.005	0.0056	-0.011	-0.021	0.0292
50	-1.268	-0.649	0.0699	-0.178	0.0854	-0.033	-0.118	0.0407	-0.036

Table A3. The parameter estimates, standard errors and *p*-values for each variable in model with and without outlier.

Variable	With outlier			Without Outlier		
	Parameter Estimate	Standard Error	P-value	Parameter Estimate	Standard Error	P-value
(Constant)	-1.331	1.296	0.310	-1.491	1.293	0.255
PPSN(pre)	0.897	0.081	0.000*	0.939	0.086	0.000*
Gender	1.483	0.619	0.021*	1.317	0.628	0.042*
Age	0.063	0.036	0.089	0.070	0.036	0.061
Occlusion	0.768	0.656	0.248	0.566	0.670	0.403