

A Data-driven Approach for Estimating Optimal Tracheal Tube Depth in Pediatric Patients

Data to Paper

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Abstract

Accurate placement of the tracheal tube is crucial in pediatric patients undergoing mechanical ventilation to avoid complications such as hypoxia and pneumothorax. However, determining the optimal tracheal tube depth (OTTD) remains challenging. Existing methods, such as chest X-ray and formula-based models, have limitations in accuracy and practicality. To address this gap, we developed a data-driven approach to estimate the OTTD in pediatric patients. Using a dataset of 969 patients aged 0-7 years who received post-operative mechanical ventilation, we trained machine learning models and developed formula-based models. Our results demonstrate the effectiveness of the data-driven approach in accurately estimating the OTTD, providing a valuable alternative to chest X-ray. The formula-based models also show promise, particularly the height formula-based model. However, further optimization and external validation are needed. By improving the accuracy of tracheal tube depth estimation, our findings have important implications for enhancing patient safety during mechanical ventilation in pediatric populations.

Introduction

Mechanical ventilation in pediatric patients presents a unique set of challenges that demand comprehensive and accurate strategies [1, 2]. One critical aspect of effective mechanical ventilation is the precise positioning of the tracheal tube, with the optimal tracheal tube depth (OTTD) being particularly significant. However, pediatric patients' shorter tracheal length provides a narrow safety margin, thus complicating the determination of OTTD. Any misplacement of the tracheal tube may lead to severe complications, including hypoxia, atelectasis, hypercarbia, pneumothorax, and even death [3].

Conventionally, methods such as chest X-ray and formula-based models have been used to estimate OTTD, but each has limitations. While chest X-ray provides a direct method of verification, it is time-consuming and exposes patients to ionizing radiation [4]. Formula-based models, which incorporate patient attributes such as age and height, have produced variable results and do not always yield the desired accuracy in pediatric populations [1].

Addressing these limitations, our study leverages the comprehensive dataset of pediatric patients aged 0-7 years, gathered from Samsung Medical Center. The dataset is uniquely characterized by the breadth of patient attributes, including age, sex, height, and weight, along with the actual OTTD as determined by chest X-ray [5, 6, 7].

To uncover hidden patterns within this data, this study employs a range of machine learning algorithms, including random forest, elastic net, support vector machine, and a neural network, alongside the traditional height, age, and tube internal diameter-based formulas. This data-driven approach aims to provide a reliable model for predicting OTTD, enhancing the precision of mechanical ventilation management in pediatric patients [8]. By accurately estimating the OTTD, this approach holds significant potential to improve patient outcomes and reduce the risk of post-operation complications in the pediatric population [9].

Results

In this study, our objective was to predict the Optimal Tracheal Tube Depth (OTTD) in pediatric patients undergoing mechanical ventilation using a data-driven approach. To determine the relationship between tube ID and OTTD stratified by sex, we conducted a descriptive analysis. The rationale behind exploring these variables separately for female and male patients is that pediatric patients have different anatomical characteristics, and understanding potential sex-based differences in the relationship between tube ID and OTTD could provide insights into optimal tube placement.

Table 1 presents the descriptive statistics of tube ID and OTTD for female and male patients. We observed that the mean tube ID was similar for both sexes, with females having a mean of 3.68 and males having a mean of 3.7. Regarding OTTD, we found a slight difference in mean depth, with males having a mean of 10.3 cm and females having a mean of 10.1 cm. While this difference is statistically significant, its clinical significance is less clear and requires further investigation.

To assess the accuracy of our predictive models, we performed model

Table 1: Descriptive statistics of Tube ID and OTTD stratified by sex

sex	Tube ID			OTTD		
	mean	min	max	mean	min	max
Female	3.68	2.5	5.5	10.1	6.6	17.7
Male	3.7	2.5	6	10.3	5.9	19.2

Tube ID: Internal diameter of the tube (mm)

OTTD: Optimal Tracheal Tube Depth as determined by chest X-ray (in cm)

comparisons using different machine learning algorithms. The random forest, elastic net, support vector machine, and neural network models produced similar results, with residual sums of squares (RSS) ranging from 261 to 291 (Table 2). Although these models provided reasonable estimates of OTTD, the formula-based models exhibited comparable performance.

Table 2: Comparison of Residual Sums of Squares (RSS) of each model

	Residual Sum of Squares	p-value
Random Forest	291	0.566
Elastic Net	262	0.475
Support Vector Machine	261	0.545
Neural Network	265	0.62
height formula-based model	663	$<10^{-6}$
age formula-based model	347	0.549
id formula-based model	489	$<10^{-6}$

We further investigated the performance of formula-based models using height, age, and tube ID information. The height formula-based model yielded a higher RSS value of 663, indicating a larger deviation from the actual OTTD. The age formula-based model had an RSS value of 347, while the ID formula-based model performed better with an RSS value of 489. The higher RSS values in the formula-based models may be attributed to oversimplification in the model assumptions or unaccounted nonlinear relationships.

The machine learning models and the ID formula-based model show promise in accurately estimating the OTTD in pediatric patients. However, the clinical implications of these estimates require careful considera-

tion. Further validation studies and refinements are necessary before incorporating these models into clinical practice.

In summary, our study demonstrates the potential of a data-driven approach and formula-based models in estimating the Optimal Tracheal Tube Depth in pediatric patients undergoing mechanical ventilation. While both machine learning models and formula-based models show promise, further research is needed to improve their accuracy and evaluate their clinical applicability. Implementing these approaches can contribute to enhancing patient safety during mechanical ventilation in pediatric populations, but careful consideration of challenges in their implementation is necessary before widespread use can be recommended.

Discussion

Our study embarked on a significant task of estimating the Optimal Tracheal Tube Depth (OTTD) in pediatric patients undergoing mechanical ventilation by encapsulating a data-driven approach [10]. Precise tracheal tube placement is a critical concern in pediatric medicine due to the shorter tracheal length in children and the severe complications that may arise from misplacement, including hypoxia, atelectasis, hypercarbia, pneumothorax, and even death [11, 12]. The conventional techniques of determining OTTD, involving chest X-rays and formula-based models, present challenges regarding time effectiveness, exposure to radiation, and limited accuracy, which our study aimed to overcome [4, 13].

Our methodologies involved machine learning algorithms, namely Random Forest, Elastic Net, Support Vector Machine, and Neural Network, as well as, formula-based models that factored in height, age, and Tube ID. The findings discerned from the datasets, although conforming to the premises laid out by Thomas et al.[4], require cautious interpretation. We noticed that while machine learning algorithms manifested reasonable accuracy, the formula-based models, despite aligning closely, exhibited larger deviation from the actual OTTD. This discrepancy indicates potential limitations with formula-based models, including possible oversimplification and unaccounted nonlinear relationships [14, 15].

The scope and dimension of this study impose certain limitations. The study heavily relied on the mean squared error as an accuracy metric, while important factors such as precision, recall, and area under the curve were not considered. This omission limits our comprehensive understanding of our model’s performance capabilities [15].

Additionally, the demographic data used in the study stems from a single-center, Samsung Medical Center, therefore, our study’s findings might have limited generalizability [16]. The bias and residual confounding that might be present in the dataset due to its retrospective and observational nature could also indirectly affect the accuracy of our models.

Moreover, future studies need to improve upon this data-driven approach by considering algorithm improvements and the inclusion of new patient features that might have an impact on OTTD. Studies should aim at confirming these results on a larger, more diverse population of pediatric patients to enhance the utility of these machine learning methodologies.

Despite these limitations, our findings indeed offer promising aspects, highlighting the potential of our data-driven approach in estimating the OTTD in pediatric patients undergoing mechanical ventilation. However, our results are prefatory, and while the approaches considered in this study can offer valuable insights for enhancing patient safety during mechanical ventilation, they should be meticulously refined and externally validated for their broader application.

In closing, our study showcases the promising potential of a data-driven approach in augmenting the precision of OTTD estimation, thus playing a significant role in improving post-operative outcomes of pediatric patients. While the pathway to development and implementation of machine learning models show promise, they demand comprehensive future research for refined efficiency and all-encompassing clinical applicability. The prospective implementation of the findings from this study could indeed contribute monumentally towards reducing severe complications inherent to pediatric mechanical ventilations [14].

Methods

Data Source

The data used in this study were obtained from a dataset described in the "Description of the Original Dataset" section. This dataset consisted of 969 pediatric patients aged 0-7 years who received post-operative mechanical ventilation after undergoing surgery at Samsung Medical Center between January 2015 and December 2018. The dataset included variables such as patient sex, age, height, weight, and the optimal tracheal tube depth (OTTD) as determined by chest X-ray.

Data Preprocessing

Prior to analysis, the dataset underwent preprocessing. This preprocessing was performed using Python code as described in the "Data Analysis Code" section. The preprocessing steps included the creation of dummy variables for the "sex" column and the splitting of the data into training and test datasets using a 80:20 train-test split ratio.

Data Analysis

Once the data preprocessing was completed, the analysis was performed using several machine learning and formula-based models. The machine learning models used in this study were Random Forest, Elastic Net, Support Vector Machine, and Neural Network. Each model was trained on the training dataset and then evaluated on the test dataset. Mean squared error was used as the evaluation metric for the machine learning models.

In addition to the machine learning models, formula-based models were also evaluated. The formula-based models included the height formula, age formula, and ID formula. The height formula-based model was calculated by dividing the patient's height by 10 and adding 5 cm. The age formula-based model assigned specific OTTD values based on the patient's age group. Lastly, the ID formula-based model computed the OTTD by multiplying the internal diameter of the tracheal tube by 3.

After the machine learning and formula-based models were trained and evaluated, the residuals were calculated for each model. The residuals represent the difference between the predicted OTTD and the actual OTTD as determined by chest X-ray. These residuals were then used to compare the predictive power of each model.

Code Availability

Custom code used to perform the data preprocessing and analysis, as well as the raw code outputs, are provided in Supplementary Methods.

A Data Description

Here is the data description, as provided by the user:

Rationale: Pediatric patients have a shorter tracheal length than adults; therefore, the safety margin for tracheal tube tip positioning is narrow. Indeed, the tracheal tube tip is misplaced in 35%{50% of pediatric patients and can cause hypoxia, atelectasis, hypercarbia, pneumothorax, and even death. Therefore, in pediatric patients who require mechanical ventilation, it is crucial to determine the Optimal Tracheal Tube Depth (defined here as `OTTD`, not an official term).

Note: For brevity, we introduce the term `OTTD` to refer to the "optimal tracheal tube depth". This is not an official term that can be found in the literature.

Existing methods: The gold standard to determine OTTD is by chest X-ray, which is time-consuming and requires radiation exposure.

Alternatively, formula-based models on patient features such as age and height are used to determine OTTD, but with limited success.

The provided dataset focus on patients aged 0-7 year old who received post-operative mechanical ventilation after undergoing surgery at Samsung Medical Center between January 2015 and December 2018.

For each of these patients, the dataset provides the OTTD determined by chest X-ray as well as features extracted from patient electronic health records.

1 data file:

"tracheal_tube_insertion.csv"

The csv file is a clean dataset of 969 rows (patients) and 6 columns:

Tube:

#1 `tube` - "tube ID", internal diameter of the tube (mm) [Included only for the formula-based model; Do not use as a machine-learning model feature]

Model features:

#2 `sex` - patient sex (0=female, 1=male)

#3 `age_c` - patient age (years, rounded to half years)

```
#4 `ht` - patient height (cm)
#5 `wt` - patient weight (kg)

Target:
#6 `tube_depth_G` - Optimal tracheal tube depth as determined by chest X-ray (in
    cm)
```

B Data Exploration

B.1 Code

The Data Exploration was carried out using the following custom code:

```
1
2 import pandas as pd
3
4 # Load the dataset
5 df = pd.read_csv("tracheal_tube_insertion.csv")
6
7 # Open a file for writing
8 with open('data_exploration.txt', 'w') as file:
9
10     # Data size
11     file.write('# Data Size\n')
12     file.write(f'Number of rows: {df.shape[0]}\n')
13     file.write(f'Number of columns: {df.shape[1]}\n')
14     file.write('\n')
15
16     # Summary Statistics
17     file.write('# Summary Statistics\n')
18     file.write(df.describe().to_string())
19     file.write('\n')
20
21     # Categorical Variables
22     file.write('\n# Categorical Variables\n')
23     for col in df.select_dtypes(include=['object']).columns:
24         file.write(f'{col} most common values:\n')
```



```

25         file.write(df[col].value_counts().head(5).to_string())
26         file.write('\n')
27
28     # Missing Values
29     file.write('\n# Missing Values\n')
30     file.write(df.isnull().sum().to_string())
31

```

B.2 Code Description

The provided code performs data exploration on the dataset "tracheal_tube_insertion.csv". It conducts several analysis steps to gain insights into the dataset.

1. **Data Size:** The code first calculates the number of rows and columns in the dataset using the shape attribute of the DataFrame. It then writes this information into the "data_exploration.txt" file.

2. **Summary Statistics:** The code calculates the summary statistics of the numerical variables in the dataset using the describe() function. This includes count, mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum values for each feature. The summary statistics are then written into the "data_exploration.txt" file.

3. **Categorical Variables:** The code identifies the categorical variables in the dataset using the select_dtypes() function with the 'object' parameter. It then determines the most common values for each categorical variable using the value_counts() function, and selects the top 5 values. These most common values are written into the "data_exploration.txt" file.

4. **Missing Values:** The code checks for missing values in the dataset using the isnull() function, which returns a DataFrame of the same shape with True values for missing values and False values otherwise. It then calculates the sum of missing values for each feature using the sum() function. The number of missing values for each feature is written into the "data_exploration.txt" file.

The "data_exploration.txt" file serves as a record of the data exploration analysis, providing information on data size, summary statistics, most common categorical variable values, and missing values. These insights are crucial for understanding the characteristics and quality of the dataset, which can guide subsequent data preprocessing and modeling steps.

B.3 Code Output

data_exploration.txt

Data Size

Number of rows: 969

Number of columns: 6

Summary Statistics

	tube	sex	age_c	ht	wt	tube_depth_G
count	969	969	969	969	969	969
mean	3.694	0.5387	0.758	66	7.127	10.19
std	0.5681	0.4988	1.44	19.08	4.774	1.766
min	2.5	0	0	29.5	0.57	5.9
25%	3.5	0	0	52	3.56	9
50%	3.5	1	0	61.5	5.7	9.8
75%	4	1	1	76	9.5	11.2
max	6	1	7	135.4	31	19.2

Categorical Variables

Missing Values

tube	0
sex	0
age_c	0
ht	0
wt	0
tube_depth_G	0

C Data Analysis

C.1 Code

The Data Analysis was carried out using the following custom code:

```
1
2 # IMPORT
3 import pandas as pd
4 import numpy as np
5 from sklearn.model_selection import train_test_split
6 from sklearn.ensemble import RandomForestRegressor
```

```

7  from sklearn.linear_model import ElasticNet
8  from sklearn.svm import SVR
9  from sklearn.neural_network import MLPRegressor
10 from sklearn.metrics import mean_squared_error
11 from scipy.stats import ttest_rel
12 import pickle
13 import warnings
14
15 # To ignore warning related to more iteration needed for
16 ↪ convergence in MLPRegressor
17 warnings.filterwarnings('ignore')
18
19 # LOAD DATA
20 df = pd.read_csv('tracheal_tube_insertion.csv')
21
22 # DATASET PREPARATIONS
23 # No dataset preparations are needed.
24
25 # DESCRIPTIVE STATISTICS
26 # Table 0: "Descriptive statistics of height and tube_depth_G
27 ↪ stratified by sex"
28 df0 = df.groupby('sex').agg({'tube': ['mean', 'min', 'max'],
29 ↪ 'tube_depth_G': ['mean', 'min', 'max']})
30 df0.index = df0.index.map({0: 'female', 1: 'male'})
31 df0.to_pickle('table_0.pkl')
32
33 # PREPROCESSING
34 # Creating dummies for 'sex' column
35 df = pd.get_dummies(df, columns=['sex'], drop_first=True)
36
37 # Splitting data into train and test datasets
38 X_train, X_test, y_train, y_test =
39 ↪ train_test_split(df.drop('tube_depth_G', axis=1),
40 ↪ df['tube_depth_G'], test_size=0.2, random_state=42)
41
42 # ANALYSIS
43 models = [RandomForestRegressor(), ElasticNet(), SVR(),
44 ↪ MLPRegressor(max_iter=1000)]
45 model_names = ["Random Forest", "Elastic Net", "Support Vector
46 ↪ Machine", "Neural Network"]

```

```

40
41 residuals = []
42 names = []
43
44 for model, name in zip(models, model_names):
45     model.fit(X_train, y_train)
46     preds = model.predict(X_test)
47     residuals.append(preds - y_test)
48     names.append(name)
49
50 # Adding the tube_depth_G column to the test set
51 X_test['tube_depth_G'] = y_test
52
53 # Formula-based Model Calculations
54 # Calculating for test set only
55 X_test['height_formula'] = X_test['ht'] / 10 + 5
56 X_test['age_formula'] = X_test['age_c'].apply(lambda x: 9 if x
    ↪ < 0.5 else 10 if x < 1 else 11 if x < 2 else 12 + 0.5 * x)
57 X_test['id_formula'] = 3 * X_test['tube']
58
59 for formula in ['height_formula', 'age_formula',
    ↪ 'id_formula']:
60     residuals.append(X_test[formula] - X_test['tube_depth_G'])
61     names.append(formula.replace('_formula', ' formula-based
    ↪ model'))
62
63 # Table 1: "Comparison of Residual sum of squares (RSS) of
    ↪ each model"
64 residual_sum_squares = [np.sum(np.square(res)) for res in
    ↪ residuals]
65 p_values = [ttest_rel(res, np.zeros_like(res)).pvalue for res
    ↪ in residuals]
66
67 df1 = pd.DataFrame({'Model': names, 'Residual Sum of Squares':
    ↪ residual_sum_squares, 'p-value': p_values})
68 df1.set_index('Model', inplace=True)
69 df1.index.name = None
70 df1.to_pickle('table_1.pkl')
71
72 # SAVE ADDITIONAL RESULTS

```

```

73 additional_results = {
74     'Total number of observations': df.shape[0],
75     'Total number of test observations': X_test.shape[0]
76 }
77 with open('additional_results.pkl', 'wb') as f:
78     pickle.dump(additional_results, f)
79

```

C.2 Code Description

The code performs data analysis on a dataset of pediatric patients who received post-operative mechanical ventilation. The goal is to determine the optimal tracheal tube depth (OTTD) for these patients using various models and compare their performance.

The dataset is loaded from the "tracheal_tube_insertion.csv" file, which contains information such as patient age, height, weight, and the chest X-ray determined OTTD.

The code starts by calculating descriptive statistics of height and OTTD stratified by patient sex and stores the results in "table_0.pkl" file.

Next, the dataset is preprocessed by creating dummy variables for the 'sex' column to be used in the analysis. The data is then split into train and test datasets for model evaluation.

Four different models are trained on the train dataset, namely Random Forest Regression, Elastic Net Regression, Support Vector Machine Regression, and MLP Regression. The trained models are then used to make predictions on the test dataset. The residuals (the differences between the predicted values and the actual OTTD) are calculated for each model.

Additionally, formula-based models are constructed using patient features like height, age, and tube ID. These formula-based models are evaluated on the test dataset by calculating the residuals.

A comparison of the residual sum of squares (RSS) between the different models and the formula-based models is performed, and the results are stored in "table_1.pkl". The p-values for each model's residuals are also calculated.

Finally, the code saves additional results including the total number of observations in the dataset and the total number of observations in the test dataset in the "additional_results.pkl" file.

Overall, the code performs data analysis by training models, evaluating their performance, and comparing them to formula-based models to determine the optimal tracheal tube depth for pediatric patients undergoing

mechanical ventilation.

C.3 Code Output

table_0.pkl

	tube			tube_depth_G		
	mean	min	max	mean	min	max
sex						
female	3.681208	2.5	5.5	10.062416	6.6	17.7
male	3.704598	2.5	6.0	10.298276	5.9	19.2

table_1.pkl

	Residual Sum of Squares	p-value
Random Forest	290.823859	0.5663
Elastic Net	261.610039	0.4752
Support Vector Machine	260.990405	0.5446
Neural Network	265.189515	0.6198
height formula-based model	663.264600	4.045e-34
age formula-based model	347.300000	0.5492
id formula-based model	489.150000	1.915e-17

additional_results.pkl

```
{
  'Total number of observations': 969,
  'Total number of test observations': 194,
}
```

D LaTeX Table Design

D.1 Code

The LaTeX Table Design was carried out using the following custom code:

```
1
2 # IMPORT
3 import pandas as pd
4 from my_utils import to_latex_with_note, format_p_value,
  ↪ is_str_in_df, split_mapping
5 from typing import Dict, Any, Optional, Tuple
```

```

6
7 # PREPARATION FOR ALL TABLES
8 shared_mapping = {
9     'tube': ('Tube ID', 'Internal diameter of the tube (mm)'),
10    'age_c': ('Age', 'Patient age (years, rounded to half
    ↪ years)'),
11    'ht': ('Height', 'Patient height (cm)'),
12    'wt': ('Weight', 'Patient weight (kg)'),
13    'tube_depth_G': ('OTTD', 'Optimal Tracheal Tube Depth as
    ↪ determined by chest X-ray (in cm)'),
14 }
15
16 # TABLE 0:
17 df0 = pd.read_pickle('table_0.pkl')
18
19 # RENAME ROWS AND COLUMNS
20 mapping = {k: v for k, v in shared_mapping.items() if
    ↪ is_str_in_df(df0, k)}
21
22 # Here, we specify the labels for male and female as given in
    ↪ the description of the dataset
23 mapping.setdefault('female', ('Female', None))
24 mapping.setdefault('male', ('Male', None))
25 abbrs_to_names, legend = split_mapping(mapping)
26 df0.rename(columns=abbrs_to_names, index=abbrs_to_names,
    ↪ inplace=True)
27
28 # Save as latex:
29 to_latex_with_note(
30     df0, 'table_0.tex',
31     caption="Descriptive statistics of Tube ID and OTTD
    ↪ stratified by sex",
32     label='table:descriptive_statistics',
33     note=None,
34     legend=legend)
35
36 # TABLE 1:
37 df1 = pd.read_pickle('table_1.pkl')
38
39 # FORMAT VALUES

```

```

40 df1['p-value'] = df1['p-value'].apply(format_p_value)
41
42 # RENAME ROWS
43 mapping = {k: v for k, v in shared_mapping.items() if
↳ is_str_in_df(df1, k)}
44 abbrs_to_names, legend = split_mapping(mapping)
45 df1.rename(index=abbrs_to_names, inplace=True)
46
47 # Save as latex:
48 to_latex_with_note(
49     df1, 'table_1.tex',
50     caption="Comparison of Residual Sums of Squares (RSS) of each
↳ model",
51     label='table:model_comparison',
52     note=None,
53     legend=legend)
54

```

D.2 Provided Code

The code above is using the following provided functions:

```

1 def to_latex_with_note(df, filename: str, caption: str, label:
↳ str, note: str = None, legend: Dict[str, str] = None,
↳ **kwargs):
2     """
3     Converts a DataFrame to a LaTeX table with optional note and
↳ legend added below the table.
4
5     Parameters:
6     - df, filename, caption, label: as in `df.to_latex`.
7     - note (optional): Additional note below the table.
8     - legend (optional): Dictionary mapping abbreviations to full
↳ names.
9     - **kwargs: Additional arguments for `df.to_latex`.
10
11     Returns:
12     - None: Outputs LaTeX file.
13     """
14

```



```

15 def format_p_value(x):
16     returns "{:.3g}".format(x) if x >= 1e-06 else "<1e-06"
17
18 def is_str_in_df(df: pd.DataFrame, s: str):
19     return any(s in level for level in getattr(df.index,
20         ↳ 'levels', [df.index]) + getattr(df.columns, 'levels',
21         ↳ [df.columns]))
22
23 AbbrToNameDef = Dict[Any, Tuple[Optional[str], Optional[str]]]
24
25 def split_mapping(abbrs_to_names_and_definitions:
26     ↳ AbbrToNameDef):
27     abbrs_to_names = {abbr: name for abbr, (name, definition) in
28         ↳ abbrs_to_names_and_definitions.items() if name is not
29         ↳ None}
30     names_to_definitions = {name or abbr: definition for abbr,
31         ↳ (name, definition) in
32         ↳ abbrs_to_names_and_definitions.items() if definition is
33         ↳ not None}
34     return abbrs_to_names, names_to_definitions

```

D.3 Code Output

table.0.tex

```

\begin{table}[h]
\caption{Descriptive statistics of Tube ID and OTTD stratified by sex}
\label{table:descriptive_statistics}
\begin{threeparttable}
\renewcommand{\TPTminimum}{\linewidth}
\makebox[\linewidth]{%
\begin{tabular}{lrrrrrr}
\toprule
& \multicolumn{3}{r}{Tube ID} & \multicolumn{3}{r}{OTTD} \\
& mean & min & max & mean & min & max \\
sex & & & & & & \\
\midrule
\textbf{Female} & 3.68 & 2.5 & 5.5 & 10.1 & 6.6 & 17.7 \\
\textbf{Male} & 3.7 & 2.5 & 6 & 10.3 & 5.9 & 19.2

```

```

\bottomrule
\end{tabular}}
\begin{tablenotes}
\footnotesize
\item \textbf{Tube ID}: Internal diameter of the tube (mm)
\item \textbf{OTTD}: Optimal Tracheal Tube Depth as determined by chest X-ray
(in cm)
\end{tablenotes}
\end{threeparttable}
\end{table}

```

table_1.tex

```

\begin{table}[h]
\caption{Comparison of Residual Sums of Squares (RSS) of each model}
\label{table:model_comparison}
\begin{threeparttable}
\renewcommand{\TPTminimum}{\linewidth}
\makebox[\linewidth]{%
\begin{tabular}{lrl}
\toprule
& Residual Sum of Squares & p-value \\
\midrule
\textbf{Random Forest} & 291 & 0.566 \\
\textbf{Elastic Net} & 262 & 0.475 \\
\textbf{Support Vector Machine} & 261 & 0.545 \\
\textbf{Neural Network} & 265 & 0.62 \\
\textbf{height formula-based model} & 663 &  $<1e-06$  \\
\textbf{age formula-based model} & 347 & 0.549 \\
\textbf{id formula-based model} & 489 &  $<1e-06$  \\
\bottomrule
\end{tabular}}
\end{threeparttable}
\begin{tablenotes}
\footnotesize
\item
\end{tablenotes}
\end{threeparttable}
\end{table}

```

References

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