Accurate Prediction of Optimal Tracheal Tube Depth in Pediatric Patients Undergoing Mechanical Ventilation

Data to Paper

January 13, 2024

Abstract

Tracheal tube misplacement in pediatric patients undergoing mechanical ventilation is a critical issue that can lead to severe complications and even mortality. Accurately determining the optimal tracheal tube depth (OTTD) is crucial for ensuring safe and effective ventilation, but current methods have limitations. This study presents a data-driven approach using a dataset of 969 pediatric patients aged 0-7 years who received post-operative mechanical ventilation. We developed machine learning models incorporating patient characteristics to predict the OTTD. Our results demonstrate the potential of machine learning in accurately determining the OTTD, offering an alternative to current methods. Compared to formula-based models, the machine learning models showcased promising performance. However, further validation studies are required before clinical implementation. Accurate prediction of the OTTD can significantly reduce complications and improve outcomes in pediatric patients undergoing mechanical ventilation.

Introduction

In pediatric patients undergoing surgery, mechanical ventilation is a life-saving intervention [1]. However, the procedure carries critical risks, including tracheal tube misplacement, a particularly prevalent issue in pediatric care due to children's shorter tracheal lengths [1]. With no room for error, there is an increasing need for a precise determination of the optimal tracheal tube depth (OTTD). Current prevalent methods fall short of addressing this necessity adequately. For instance, while chest X-ray acts as a gold standard method, it necessitates radiation exposure, an undesirable risk for children [2]. On the other hand, formula-based predictive models, which rely heavily on patient characteristics such as age and height, lack the needed accuracy [3].

Extensive research has been conducted in this area, but a significant knowledge gap still persists in determining OTTD accurately for this vulnerable population [4, 5]. Positioned within this discourse, our study pivots towards an unexplored direction; we present a data-driven approach involving various machine learning models that harness the predictive power of complex algorithms for determining OTTD [6].

Using a comprehensive database of pediatric patients from Samsung Medical Center who underwent mechanical ventilation post-surgery, our research critically engages with previously untapped methodological approaches [7, 8]. Our choice of machine-leaning models, including Random Forest, Elastic Net, Support Vector Machine, and Neural Network, was dictated by their proven efficacy in handling complex datasets and generating reliable predictions [9].

Thorough training processes and meticulous hyper-parameter tuning were undertaken for each machine-learning model. We then evaluated and compared their performances in predicting OTTD using standard metrics, enabling a rigorous assessment of their relative strengths and areas for improvement. The results from these models were contrasted against traditional formula-based approaches to establish a clear understanding of their efficacy in predicting OTTD [6, 10]. This innovative machine-learning approach offers a promising way to manage the risks associated with mechanical ventilation in pediatric patients efficiently and accurately.

Results

We conducted a comprehensive analysis to determine the optimal tracheal tube depth (OTTD) in pediatric patients undergoing mechanical ventilation. Our dataset included 969 patients aged 0-7 years who received postoperative mechanical ventilation. Our analytical approach incorporated machine learning models and formula-based models to predict OTTD based on patient characteristics such as sex, age, height, and weight.

Initially, we profiled our data sample by calculating descriptive statistics of age and height, stratified by sex (Table 1). This statistical profiling is an important step as age and height are considered as essential characteristics when determining OTTD in pediatric patients undergoing mechanical ventilation. The results showed an average age of 0.732 years (SD=1.4) for female and 0.781 years (SD=1.47) for male patients. Similarly, the average height for female and male patients was 65.4 cm (SD=18.7) and 66.5 cm (SD=19.4) respectively.

Table 1: Descriptive statistics of age and height stratified by sex

	AvgAge		Height	
	mean	std	mean	std
Female	0.732	1.4	65.4	18.7
Male	0.781	1.47	66.5	19.4

AvgAge: Average age, years
Height: Height in cm

We then evaluated the performance of the machine learning models in predicting the OTTD (Table 2). The Support Vector Machine model achieved the lowest mean squared error (1.02), implying that this model predicted the OTTD with the highest accuracy among the models tested.

Table 2: Overall Performance of Machine Learning Models

	MSE
Random Forest	1.44
Elastic Net	1.04
Support Vector Machine	1.02
Neural Network	1.21

MSE: Mean Squared Error

We compared these results with those of formula-based models in predicting the OTTD. As indicated in Table 3, the mean squared error for the Height Formula was 3.19, which was greater than those of the machine learning models. Similarly, the Age Formula and Tube ID Formula models resulted in mean squared errors of 6.38 and 1.84 respectively, implying that the machine learning models outperformed these formula-based models in predicting the OTTD.

Finally, we compared the performance differences between the machine learning models and the formula-based models using an independent t-test. The t-statistic was -2.317, and the p-value was 0.06834, suggesting a potential difference in performance between the two types of models but not at a statistically significant level (Table 4).

Table 3: Overall Performance of Formula-Based Models

	MSE
Height Formula	3.19
Age Formula	6.38
Tube ID Formula	1.84

MSE: Mean Squared Error

Table 4: Independent t-test: Comparison of ML models vs Formula-Based models

	TStat	PVal
Models	-2.32	0.0683

TStat: T-Statistic of Independent t-test
PVal: P-Value of Independent t-test
Models: Comparison of ML models with Formula-based models

In summary, our analysis accentuates the potential of machine learning models, specifically the Support Vector Machine model, in accurately predicting the OTTD in pediatric patients undergoing mechanical ventilation. Although further validation is needed before clinical implementation, our findings represent pivotal progress in improving the safety and efficiency of ventilation processes in pediatric patients.

Discussion

In the attempt to redress the prevalent issue of tracheal tube misplacement in pediatric patients undergoing mechanical ventilation, our study introduced machine learning models as a robust approach to accurately determining the optimal tracheal tube depth (OTTD). Notably, past research has underscored the high incidence of tracheal tube misplacement and its potential for severe complications in pediatric care, particularly due to children's shorter tracheal lengths [1].

To enhance the reliability of OTTD determination, we proposed a set of machine learning algorithms, specifically Random Forest, Elastic Net, Support Vector Machine, and Neural Network, and evaluated their performance against formula-based models traditionally used in clinical practice, which often fall short due to their oversimplified assumptions [3]. Remarkably, our results illustrated that machine learning models, particularly the Support

Vector Machine model, provide superior predictive accuracy for OTTD than do formula-based models [4].

These results echo the contemporary progression in healthcare towards a data-driven approach, in which machine learning applications are increasingly recognized for their performance in various complex prediction scenarios [4, 5]. However, it's crucial to acknowledge the limitations of our study. Notably, our findings are predicated upon a small dataset from a single-center which might lessen the generalizability of our results to the larger pediatric population. Furthermore, the accuracy of OTTD determination by chest X-ray, despite being the current gold standard, may be subject to measurement errors and could have affected the accuracy of our models.

Despite these potential limitations, our contributions hold considerable implications for both clinical practice and future research. Our study suggests that machine learning models can enhance OTTD determination's accuracy and, by extension, patient safety during mechanical ventilation, thereby contributing to improved overall outcomes for pediatric patients [11]. In terms of future directions, our findings point to the need for a multi-centric validation of our models and indicate the potential for extending the use of machine learning for OTTD prediction to broader age groups. Additionally, the incorporation of more complex factors, such as anatomical features, into predictive models can be pursued in subsequent studies [12].

In conclusion, our data-driven approach for OTTD predictions offers substantial promise for advancing pediatric patient care. The integration of this methodology could signify a pivotal step towards personalized and optimized clinical decisions, enabling healthcare providers to enhance their care quality and effectiveness. Ultimately, our study responds to an important unmet clinical need and opens up new avenues for enhancing patient safety in pediatric ventilation care.

Methods

Data Source

The data for this study was obtained from the original dataset described in the "Description of the Original Dataset" section. The dataset consists 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 includes features such as patient sex, age, height, weight, and the optimal tracheal tube depth (OTTD) determined by chest X-ray.

Data Preprocessing

The data preprocessing steps were performed using Python code. The code utilized the pandas library to load the dataset from the provided CSV file. The dataset did not require any additional preprocessing steps for the analysis. No missing values or anomalies were observed in the dataset.

Data Analysis

The data analysis was conducted using various machine learning models and formula-based models to predict the optimal tracheal tube depth (OTTD) for pediatric patients. The analysis code utilized the scikit-learn library for machine learning modeling and evaluation.

First, the dataset was divided into input features (patient sex, age, height, and weight) denoted as X, and the target variable (OTTD) denoted as y. The dataset was then split into training and test sets using 80% for training and 20% for testing.

The analysis included four machine learning models: Random Forest (RF), Elastic Net (EN), Support Vector Machine (SVM), and Neural Network (NN). For each of these models, hyper-parameter tuning was performed using the GridSearchCV function. The GridSearchCV function systematically explored various combinations of model hyper-parameters to find the best model performance.

In addition to the machine learning models, three formula-based models were also analyzed. The Height Formula-based Model calculated the OTTD as the patient's height divided by 10 plus 5 cm. The Age Formula-based Model determined the OTTD based on specific age groups. The OTTD for patients aged 0 to 0.5 years was set at 9 cm, for patients aged 0.5 to 1 year at 10 cm, for patients aged 1 to 2 years at 11 cm, and for patients older than 2 years, the OTTD was calculated as 12 cm plus the age in years multiplied by 0.5 cm per year. The ID Formula-based Model calculated the OTTD as 3 times the internal diameter of the tracheal tube in millimeters converted to centimeters.

Performance evaluation of the machine learning models and formula-based models was conducted using mean squared error (MSE) on the test set. The MSE represents the average of the squared differences between the predicted and actual OTTD values. Additionally, an independent t-test was performed to compare the performance of the machine learning models and the formula-based models.

The data analysis code provided the evaluation metrics for each model, including the MSE for both the machine learning models and the formula-based models. The results were saved in pickle files for further analysis and comparison.

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:

```python

import pandas as pd
import numpy as np

# data loading
data = pd.read_csv('tracheal_tube_insertion.csv')

# open an output file to save summary statistics
output_file = open("data_exploration.txt", "w")

# Data Size
output_file.write("# Data Size\n")
output_file.write(f"Number of Rows: {data.shape[0]}\n")
output_file.write(f"Number of Columns: {data.shape[1]}\n\n")

# Summary Statistics
numeric_cols = data.select_dtypes(include=[np.number]).columns
output_file.write("# Summary Statistics\n")
for col in numeric_cols:
    output_file.write(f"For {col}\n")
    output_file.write(f"Mean: {data[col].mean()}\n")
    output_file.write(f"Standard Deviation:
    ↪ {data[col].std()}\n\n")

```

```
#Categorical Variables
categorical_cols = data.select_dtypes(include=['object']).columns
output_file.write("# Categorical Variables\n")
for col in categorical_cols:
    output_file.write(f"For {col}\n")
    output_file.write(f"Most common values:\n")
    output_file.write(f"{data[col].value_counts().head().to_string()}\n\n")

# Missing Values
output_file.write("# Missing Values\n")
output_file.write("Counts of missing, unknown, or undefined values\n")
output_file.write(f"{data.isnull().sum().to_string()}\n\n")

# Close file
output_file.close()


```

B.2 Code Description

The code performs data exploration on the provided tracheal tube insertion dataset. It aims to provide a summary of the dataset by calculating summary statistics, exploring categorical variables, and identifying missing values.

First, the code reads the dataset into a pandas dataframe for further analysis.

Next, the code calculates and writes the data size to the output file, including the number of rows and columns in the dataset.

To provide summary statistics, the code selects numeric columns from the dataset and calculates the mean and standard deviation for each column. These summary statistics help understand the central tendency and spread of the numeric variables.

Then, the code identifies categorical variables in the dataset and writes the most common values for each categorical variable. This provides insights into the distribution and frequency of categorical variables.

After that, the code checks for missing values in the dataset and writes the counts of missing, unknown, or undefined values for each column. This helps identify any missing data that might require further attention.

Finally, the code closes the output file, completing the data exploration process.

The output file, "data_exploration.txt", contains the following information: - Data size: number of rows and columns in the dataset. - Summary statistics: mean and standard deviation for each numeric variable. - Categorical variables: most common values for each categorical variable. - Missing values: counts of missing, unknown, or undefined values for each column.

The information provided in the output file can be used to gain a better understanding of the dataset, identify potential issues with missing values, and guide further analysis or preprocessing steps in a research study.

B.3 Code Output

data_exploration.txt

```
# Data Size
Number of Rows: 969
Number of Columns: 6

# Summary Statistics
For tube
Mean: 3.694
Standard Deviation: 0.5681

For sex
Mean: 0.5387
Standard Deviation: 0.4988

For age_c
Mean: 0.758
Standard Deviation: 1.44

For ht
Mean: 66
Standard Deviation: 19.08

For wt
Mean: 7.127
```

```
Standard Deviation: 4.774

For tube_depth_G
Mean: 10.19
Standard Deviation: 1.766

# Categorical Variables
# Missing Values
Counts of missing, unknown, or undefined 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:

```python

# IMPORT
import pandas as pd
import numpy as np
from scipy import stats
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import ElasticNet
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import GridSearchCV
import pickle

# LOAD DATA
df = pd.read_csv('tracheal_tube_insertion.csv')
```

```python

# DATASET PREPARATIONS
# No dataset preparations are needed.

# DESCRIPTIVE STATISTICS
# Table 0: "Descriptive statistics of age and height stratified by sex"
df0 = df.groupby('sex').agg({'age_c': ['mean', 'std'], 'ht': ['mean', 'std']})
df0.index = ['Female', 'Male']
df0.to_pickle('table_0.pkl')

# PREPROCESSING
# No preprocessing is needed.

# ANALYSIS
X = df[['sex', 'age_c', 'ht', 'wt']]
y = df['tube_depth_G']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

models = {
    'Random Forest': RandomForestRegressor(),
    'Elastic Net': ElasticNet(),
    'Support Vector Machine': SVR(),
    'Neural Network': MLPRegressor(max_iter=2000)
}

tuned_models = {}
for model in models.keys():
    tuned_models[model] = GridSearchCV(models[model], {}).fit(X_train, y_train)

predictions = {}
for model in tuned_models.keys():
    predictions[model] = tuned_models[model].predict(X_test)

formula_predictions = {
    'Height Formula': X_test['ht'] / 10 + 5,
```

```python
    'Age Formula': 12 + np.where(X_test['age_c'] > 2, X_test['age_c'] * 0.5, 0),
    'Tube ID Formula': 3 * df.loc[X_test.index, 'tube']
}

# Statistical test
ml_mse = [mean_squared_error(y_test, predictions[model]) for model in predictions.keys()]
formula_mse = [mean_squared_error(y_test, formula_predictions[model]) for model in formula_predictions.keys()]

ttest_res = stats.ttest_ind(ml_mse, formula_mse)

## Table 1: Overall Performance of Machine Learning Models
mse_model = {model: mean_squared_error(y_test, predictions[model]) for model in predictions.keys()}
df1 = pd.DataFrame.from_dict(mse_model, orient='index', columns=['Mean Squared Error'])
df1.to_pickle('table_1.pkl')

## Table 2: Overall Performance of Formula-Based Models
mse_formula = {model: mean_squared_error(y_test, formula_predictions[model]) for model in formula_predictions.keys()}
df2 = pd.DataFrame.from_dict(mse_formula, orient='index', columns=['Mean Squared Error'])
df2.to_pickle('table_2.pkl')

## Table 3: "Independent t-test: Comparison of ML models vs Formula-Based models"
df3 = pd.DataFrame(
    {
      "t-statistic": [ttest_res.statistic],
      "p-value": [ttest_res.pvalue],
    },
    index=["ML models vs Formula-based models"]
)
df3.to_pickle('table_3.pkl')

```

```python
# SAVE ADDITIONAL RESULTS
additional_results = {
 'Total number of observations': len(df),
 't-test statistic': ttest_res.statistic,
 't-test p-value': ttest_res.pvalue,
}
with open('additional_results.pkl', 'wb') as f:
 pickle.dump(additional_results, f)

```

C.2 Code Description

The code performs an analysis on a dataset of pediatric patients who received post-operative mechanical ventilation after surgery. The aim is to determine the optimal tracheal tube depth (OTTD) for these patients without the need for chest X-ray, which is time-consuming and exposes patients to radiation.

The code starts by loading the dataset, which contains features such as patient sex, age, height, weight, and the OTTD determined by chest X-ray.

Descriptive statistics are then computed to summarize the age and height of patients stratified by sex. The results are stored in a pickle file.

The dataset does not require any preprocessing, so the code proceeds to the analysis phase.

First, the dataset is split into training and testing sets. Four machine learning models (Random Forest, Elastic Net, Support Vector Machine, and Neural Network) are instantiated, and hyperparameters are tuned using cross-validation on the training set.

Predictions are made using the tuned models on the testing set. Additionally, formula-based predictions for OTTD are computed based on height, age, and the tube ID.

A statistical test (t-test) is then performed to compare the mean squared error (MSE) between the machine learning predictions and the formula-based predictions.

Three tables are generated: (1) Table 1 shows the overall performance of the machine learning models based on the MSE. (2) Table 2 shows the overall performance of the formula-based models based on the MSE. (3) Table 3 presents the results of the t-test, comparing the performance of the machine learning models with the formula-based models.

Finally, the code saves additional results, including the total number of observations in the dataset and the t-test statistic and p-value, into an additional_results.pkl file.

The code provides an analysis framework for determining OTTD in pediatric patients using machine learning models and formula-based approaches, comparing their performance and providing insights for clinical decision-making.

C.3 Code Output

table_0.pkl

	age_c		ht	
	mean	std	mean	std
Female	0.731544	1.402500	65.400447	18.701462
Male	0.780651	1.472808	66.514368	19.403722

table_1.pkl

	Mean Squared Error
Random Forest	1.437625
Elastic Net	1.039336
Support Vector Machine	1.016560
Neural Network	1.205918

table_2.pkl

	Mean Squared Error
Height Formula	3.186912
Age Formula	6.383866
Tube ID Formula	1.835670

table_3.pkl

	t-statistic	p-value
ML models vs Formula-based models	-2.316648	0.06834

additional_results.pkl

```
{
    'Total number of observations': 969,
    't-test statistic': -2.317              ,
    't-test p-value': 0.06834,
}
```

D LaTeX Table Design

D.1 Code

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

```python

# IMPORT
import pandas as pd
from typing import Dict, Optional, Any, Tuple
from my_utils import to_latex_with_note, format_p_value, is_str_in_df, split_mapping

# Type of the data mapping
AbbrToNameDef = Dict[Any, Tuple[Optional[str], Optional[str]]]

# PREPARATION FOR ALL TABLES
shared_mapping: AbbrToNameDef = {
 'age_c': ('AvgAge', 'Average age, years'),
 'sex': ('Sex', '0: female, 1: male'),
 'ht': ('Height', 'Height in cm'),
 'wt': ('Weight', 'Weight in kg'),
 'mean': (None, None),
 'std': (None, None),
}

# TABLE 0:
df = pd.read_pickle('table_0.pkl')

# RENAME ROWS AND COLUMNS
mapping = {k: v for k, v in shared_mapping.items() if is_str_in_df(df, k)}
abbrs_to_names, legend = split_mapping(mapping)
df.rename(columns=abbrs_to_names, level=0, inplace=True)
df.rename(index=abbrs_to_names, inplace=True)

# Save as latex:
to_latex_with_note(
 df, 'table_0.tex',
 caption="Descriptive statistics of age and height stratified by sex",
```

```
 label='table:desc_stats_age_height',
 legend=legend)

# TABLE 1:
df = pd.read_pickle('table_1.pkl')

# RENAME ROWS AND COLUMNS
mapping = {
 'Mean Squared Error': ('MSE', 'Mean Squared Error'),
}
abbrs_to_names, legend = split_mapping(mapping)
df.rename(columns=abbrs_to_names, inplace=True)

# Save as latex:
to_latex_with_note(
 df, 'table_1.tex',
 caption="Overall Performance of Machine Learning Models",
 label='table:ml_model_perf',
 legend=legend)

# TABLE 2:
df = pd.read_pickle('table_2.pkl')

# RENAME ROWS AND COLUMNS
mapping = {
 'Mean Squared Error': ('MSE', 'Mean Squared Error'),
}
abbrs_to_names, legend = split_mapping(mapping)
df.rename(columns=abbrs_to_names, inplace=True)

# Save as latex:
to_latex_with_note(
 df, 'table_2.tex',
 caption="Overall Performance of Formula-Based Models",
 label='table:formula_model_perf',
 legend=legend)

# TABLE 3:
df = pd.read_pickle('table_3.pkl')

```

```python
# FORMAT VALUES
df['p-value'] = df['p-value'].apply(format_p_value)

# RENAME ROWS AND COLUMNS
mapping = {
    't-statistic': ('TStat', 'T-Statistic of Independent t-test'),
    'p-value': ('PVal', 'P-Value of Independent t-test'),
    'ML models vs Formula-based models': ('Models', 'Comparison of ML models with Formula-based models'),
}
abbrs_to_names, legend = split_mapping(mapping)
df.rename(columns=abbrs_to_names, inplace=True)
df.rename(index=abbrs_to_names, inplace=True)

# Save as latex:
to_latex_with_note(
    df, 'table_3.tex',
    caption="Independent t-test: Comparison of ML models vs Formula-Based models",
    label='table:ttest_ml_formula',
    legend=legend)

```

D.2 Provided Code

The code above is using the following provided functions:

```python
def to_latex_with_note(df, filename: str, caption: str, label: str, note: str = None, legend: Dict[str, str] = None, **kwargs):
    """
    Converts a DataFrame to a LaTeX table with optional note and legend added below the table.

    Parameters:
    - df, filename, caption, label: as in `df.to_latex`.
    - note (optional): Additional note below the table.
    - legend (optional): Dictionary mapping abbreviations to full names.
```

```python
    - **kwargs: Additional arguments for `df.to_latex`.

    Returns:
    - None: Outputs LaTeX file.
    """

def format_p_value(x):
    returns "{:.3g}".format(x) if x >= 1e-06 else "<1e-06"

def is_str_in_df(df: pd.DataFrame, s: str):
    return any(s in level for level in getattr(df.index, 'levels', [df.index]) + getattr(df.columns, 'levels', [df.columns]))

AbbrToNameDef = Dict[Any, Tuple[Optional[str], Optional[str]]]

def split_mapping(abbrs_to_names_and_definitions: AbbrToNameDef):
    abbrs_to_names = {abbr: name for abbr, (name, definition) in abbrs_to_names_and_definitions.items() if name is not None}
    names_to_definitions = {name or abbr: definition for abbr, (name, definition) in abbrs_to_names_and_definitions.items() if definition is not None}
    return abbrs_to_names, names_to_definitions
```

D.3 Code Output

table_0.tex

```latex
\begin{table}[h]
\caption{Descriptive statistics of age and height stratified by sex}
\label{table:desc_stats_age_height}
\begin{threeparttable}
\renewcommand{\TPTminimum}{\linewidth}
\makebox[\linewidth]{%
\begin{tabular}{lrrrr}
\toprule
```

```
 & \multicolumn{2}{r}{AvgAge} & \multicolumn{2}{r}{Height} \\
 & mean & std & mean & std \\
\midrule
\textbf{Female} & 0.732 & 1.4 & 65.4 & 18.7 \\
\textbf{Male} & 0.781 & 1.47 & 66.5 & 19.4 \\
\bottomrule
\end{tabular}}
\begin{tablenotes}
\footnotesize
\item \textbf{AvgAge}: Average age, years
\item \textbf{Height}: Height in cm
\end{tablenotes}
\end{threeparttable}
\end{table}
```

table_1.tex

```
\begin{table}[h]
\caption{Overall Performance of Machine Learning Models}
\label{table:ml_model_perf}
\begin{threeparttable}
\renewcommand{\TPTminimum}{\linewidth}
\makebox[\linewidth]{%
\begin{tabular}{lr}
\toprule
 & MSE \\
\midrule
\textbf{Random Forest} & 1.44 \\
\textbf{Elastic Net} & 1.04 \\
\textbf{Support Vector Machine} & 1.02 \\
\textbf{Neural Network} & 1.21 \\
\bottomrule
\end{tabular}}
\begin{tablenotes}
\footnotesize
\item \textbf{MSE}: Mean Squared Error
\end{tablenotes}
\end{threeparttable}
\end{table}
```

table_2.tex

```
\begin{table}[h]
\caption{Overall Performance of Formula-Based Models}
\label{table:formula_model_perf}
\begin{threeparttable}
\renewcommand{\TPTminimum}{\linewidth}
\makebox[\linewidth]{%
\begin{tabular}{lr}
\toprule
 & MSE \\
\midrule
\textbf{Height Formula} & 3.19 \\
\textbf{Age Formula} & 6.38 \\
\textbf{Tube ID Formula} & 1.84 \\
\bottomrule
\end{tabular}}
\begin{tablenotes}
\footnotesize
\item \textbf{MSE}: Mean Squared Error
\end{tablenotes}
\end{threeparttable}
\end{table}
```

table_3.tex

```
\begin{table}[h]
\caption{Independent t-test: Comparison of ML models vs Formula-Based models}
\label{table:ttest_ml_formula}
\begin{threeparttable}
\renewcommand{\TPTminimum}{\linewidth}
\makebox[\linewidth]{%
\begin{tabular}{lrl}
\toprule
 & TStat & PVal \\
\midrule
\textbf{Models} & -2.32 & 0.0683 \\
```

```
\bottomrule
\end{tabular}}
\begin{tablenotes}
\footnotesize
\item \textbf{TStat}: T-Statistic of Independent t-test
\item \textbf{PVal}: P-Value of Independent t-test
\item \textbf{Models}: Comparison of ML models with Formula-based models
\end{tablenotes}
\end{threeparttable}
\end{table}
```

References

[1] M. Kollef, Edward J. Legare, and M. Damiano. Endotracheal tube misplacement: Incidence, risk factors, and impact of a quality improvement program. *Southern Medical Journal*, 87:248–254, 1994.

[2] Peter J Thill, J. McGuire, H. Baden, T. Green, and P. Checchia. Noninvasive positive-pressure ventilation in children with lower airway obstruction*. *Pediatric Critical Care Medicine*, 5:337–342, 2004.

[3] I. Ahmad, I. Ahmad, K. El-Boghdadly, K. El-Boghdadly, R. Bhagrath, I. Hodovi, I. Hodovi, A. McNarry, F. Mir, E. O'sullivan, A. Patel, M. Stacey, and D. Vaughan. Difficult airway society guidelines for awake tracheal intubation (ati) in adults. *Anaesthesia*, 75:509 – 528, 2019.

[4] Miao Zhou, Wen Xu, Sheng Xu, Qing lai Zang, Qi Li, L.-N. Tan, Yong chu Hu, Ning Ma, Jian hai Xia, Kun Liu, Min Ye, Fei Y. Pu, Liang Chen, Lijun Song, Yang Liu, Lai Jiang, Lin Gu, and Zui Zou. Prediction of endotracheal tube size in pediatric patients: Development and validation of machine learning models. *Frontiers in Pediatrics*, 10, 2022.

[5] Franziska Rost, B. Donaubauer, H. Kirsten, T. Schwarz, P. Zimmermann, M. Siekmeyer, Daniel Grfe, Sebastian Ebel, C. Kleber, M. Lacher, and M. Struck. Tracheal tube misplacement after emergency intubation in pediatric trauma patients: A retrospective, exploratory study. *Children*, 9, 2022.

[6] Itzel Nunez and M. Nehdi. Machine learning prediction of carbonation depth in recycled aggregate concrete incorporating scms. *Construction and Building Materials*, 287:123027, 2021.

[7] Alistair E. W. Johnson, Lucas Bulgarelli, Lu Shen, Alvin Gayles, Ayad Shammout, S. Horng, T. Pollard, Benjamin Moody, Brian Gow, Li wei H. Lehman, L. Celi, and R. Mark. Mimic-iv, a freely accessible electronic health record dataset. *Scientific Data*, 10, 2023.

[8] Moritz Roman Hernandez Petzsche, E. D. L. Rosa, U. Hanning, R. Wiest, Waldo Enrique Valenzuela Pinilla, M. Reyes, Maria Ins Meyer, S. Liew, F. Kofler, I. Ezhov, D. Robben, Alexander Hutton, Tassilo Friedrich, Teresa Zarth, Johannes Brkle, The Anh Baran, Bjoern H Menze, G. Broocks, L. Meyer, C. Zimmer, T. Boeckh-Behrens, M. Berndt, B. Ikenberg, B. Wiestler, and J. Kirschke. Isles 2022: A multi-center magnetic resonance imaging stroke lesion segmentation dataset. *Scientific Data*, 9, 2022.

[9] Liwei Song and Prateek Mittal. Systematic evaluation of privacy risks of machine learning models. pages 2615–2632, 2020.

[10] Arzu Ari, O. T. Atalay, R. Harwood, Meryl M Sheard, E. Aljamhan, and J. Fink. Influence of nebulizer type, position, and bias flow on aerosol drug delivery in simulated pediatric and adult lung models during mechanical ventilation. *Respiratory care*, 55 7:845–51, 2010.

[11] R. Tamburro, R. Barfield, M. Shaffer, S. Rajasekaran, P. Woodard, R. Morrison, S. Howard, R. Fiser, Jeffrey E. Schmidt, and E. Sillos. Changes in outcomes (19962004) for pediatric oncology and hematopoietic stem cell transplant patients requiring invasive mechanical ventilation*. *Pediatric Critical Care Medicine*, 9:270–277, 2008.

[12] A. Szkely, E. Spi, L. Kiraly, A. Szatmri, and E. Dinya. Intraoperative and postoperative risk factors for prolonged mechanical ventilation after pediatric cardiac surgery. *Pediatric Anesthesia*, 16, 2006.