



# MedicalMatch

**One-time Shifts. Anytime. Anywhere.**

## Capstone Project: Healthcare Attrition Analysis

By: Tanya Seegmiller

As an incoming data scientist on MedicalMatch's product solutions team, my objective is to analyze healthcare attrition data to identify key trends and at-risk groups. By quantifying the financial impact of attrition on hospitals, clinics and nursing homes, I will provide critical insights that will empower our marketing team to develop targeted campaigns enhancing retention and operational efficiency in the healthcare sector.



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**Problem:** Healthcare Facilities are understaffed and clinicians are burnt out. Resignations have increased 66% in the last 3 years and there is a projected shortfall of 3.2 Million workers by 2026



**Ratio of labor costs to  
total facility expenses**

**62%**



**Cost to facilities to hire  
and onboard new  
clinicians**

**CNA: \$16,000  
RN: \$56,000  
Doctor: \$500k- \$1M**



**Clinicians that report a  
“high level” of burnout.**

**46%**

# Table of Contents

## Data Collection and Cleaning

### Data Source:

Excel Bi Analytics

### Data Info:

Rows: 60,000

Columns: 25

### Data Cleaning:

Research & customize  
healthcare specific feature  
ratios.

## Exploratory Data Analysis

### EDA Goals:

- Identify key trends and at-risk groups.
- Quantify the financial impact of attrition on the market to develop a targeted marketing strategy.

## Model Building & Scoring Metrics

### Model Type:

This is a binary classification problem. All classification models will be tested.

### Model Performance Criteria:

- False Negatives will contribute to high attrition costs.
- Recall will be our performance metric

## Conclusions and Recommendation

No spoilers folks!  
You'll have to wait  
until the end of the  
show to find out

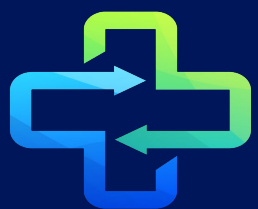


## Age Categories:

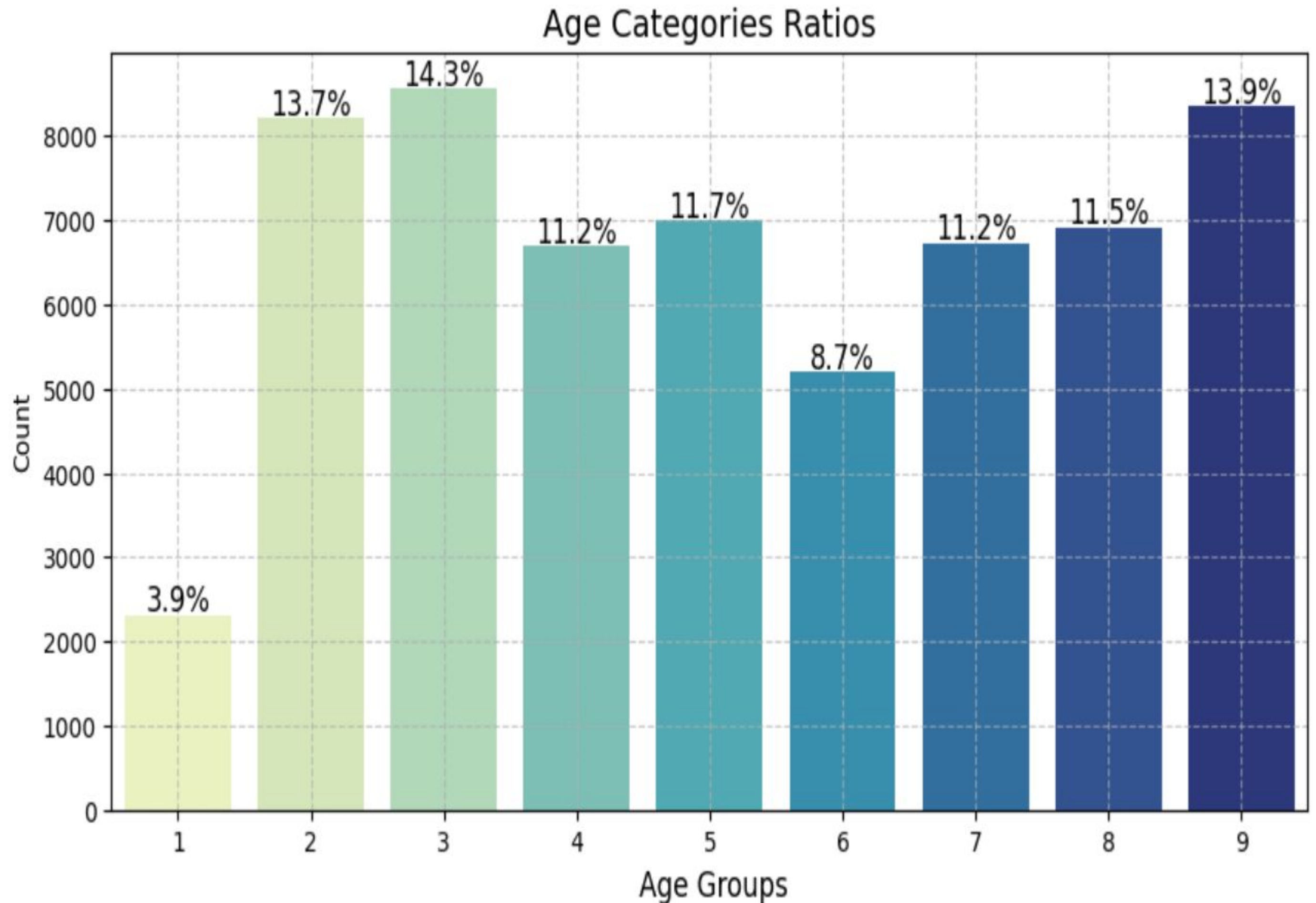
- 1: >30 yrs
- 2: 30-34 yrs
- 3: 35-39 yrs
- 4: 40-44 yrs
- 5: 45-49 yrs
- 6: 50-54 yrs
- 7: 55-59 yrs
- 8: 60-64 yrs
- 9: 65+ yrs

## Observations:

- 36% of the workforce is 55+ yrs old.
- 25.4% are 60+



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	attrition	0	1
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	age
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1	69.542709	30.457291
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2	78.909578	21.090422
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3	89.809735	10.190265
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4	89.907435	10.092565
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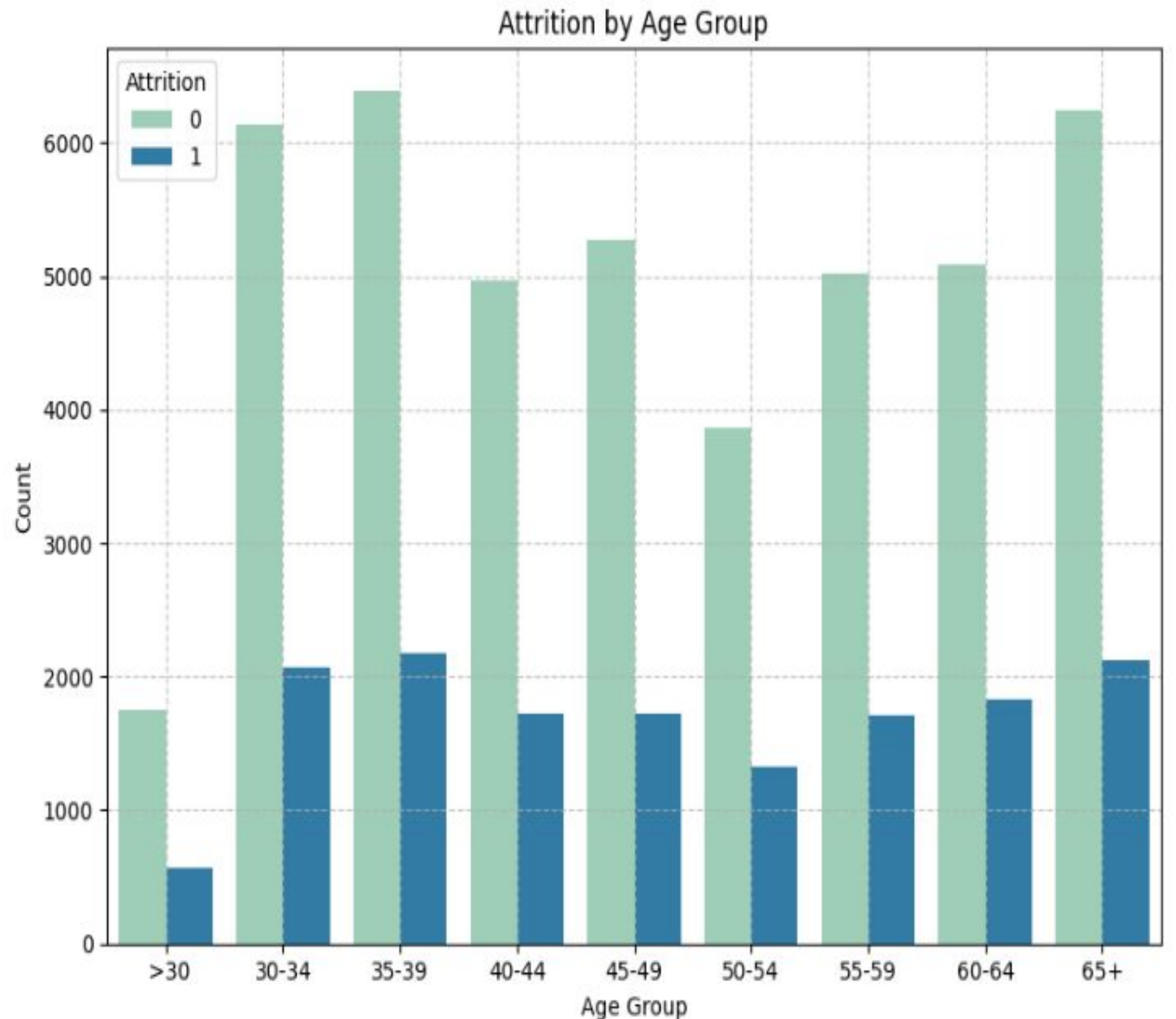
5	90.810347	9.189653
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6	88.514813	11.485187
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7	82.909793	17.090207
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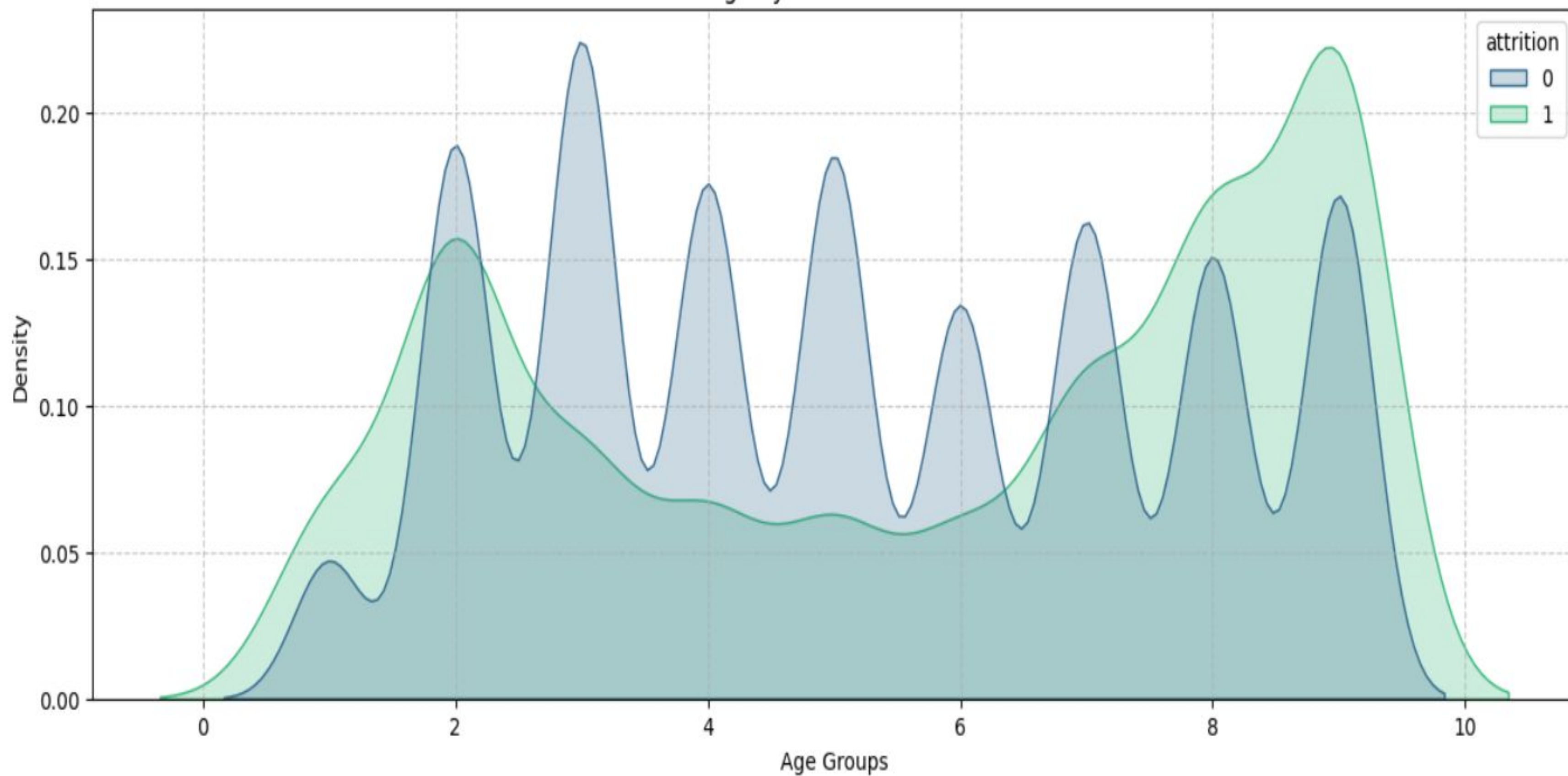
8	74.710816	25.289184
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9	70.502392	29.497608
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Age Category

Age by Attrition Status



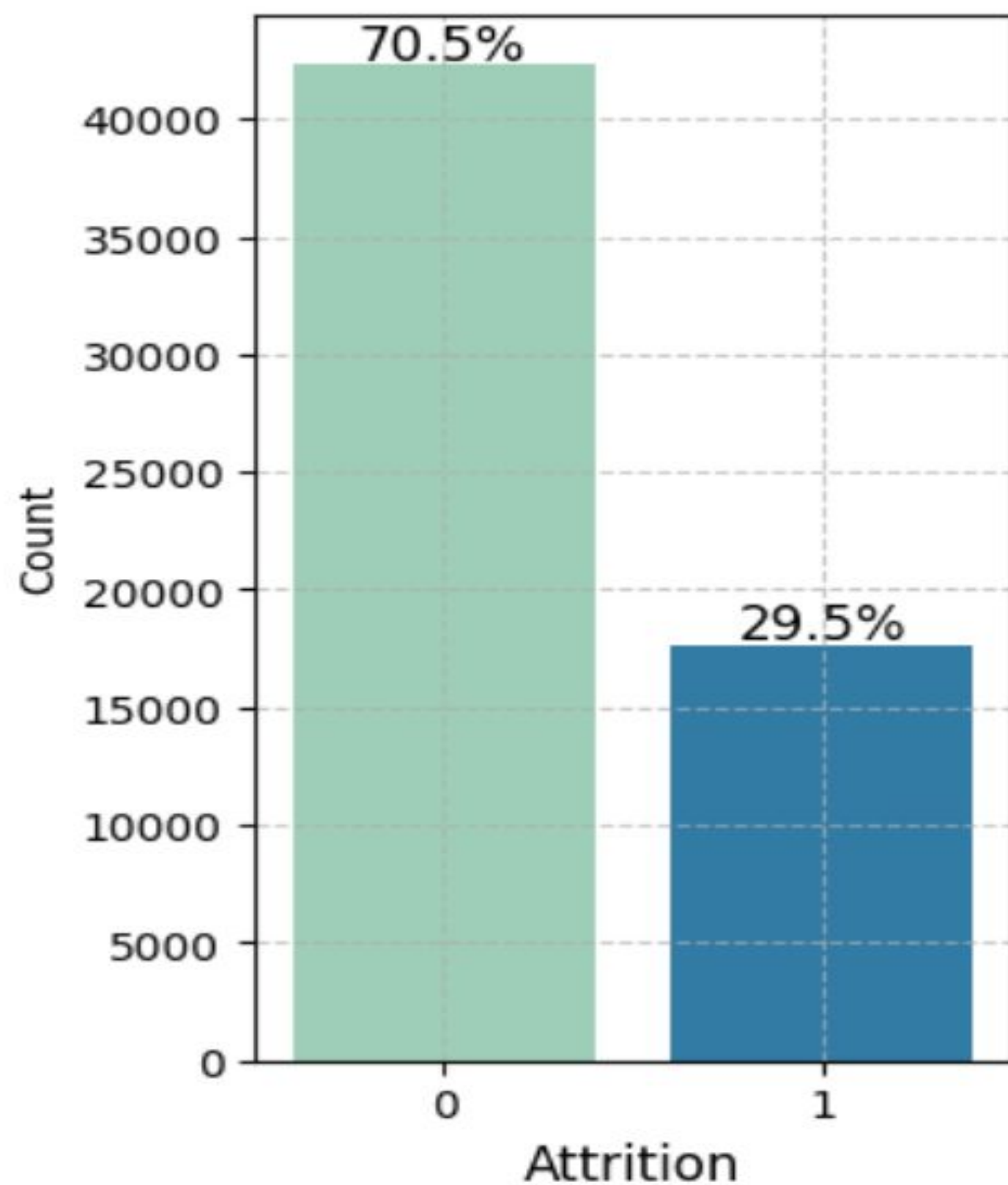


# Welcome To The Great Healthcare Paradox

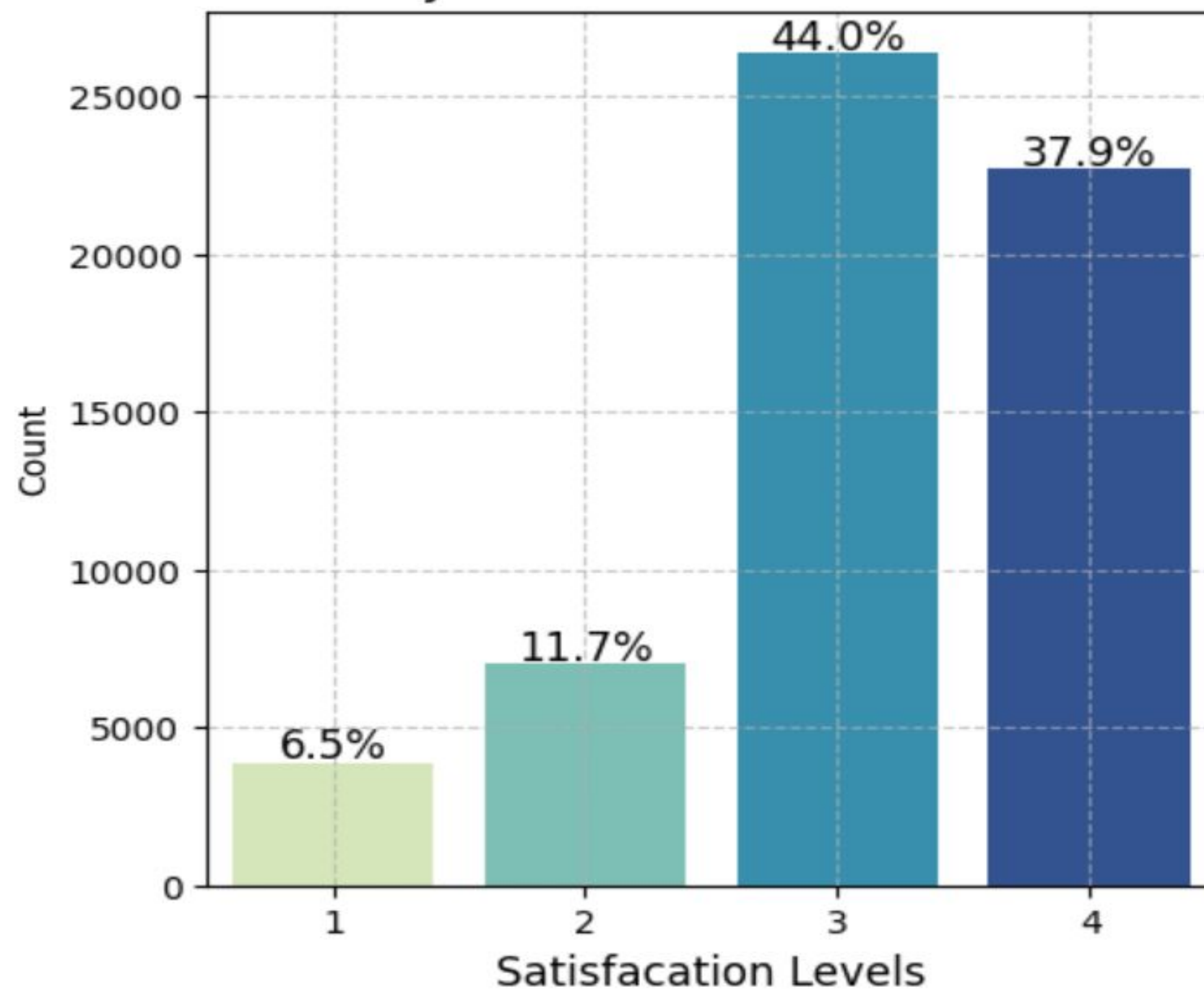


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## Healthcare Attrition Ratio



## Job Satisfaction Ratios





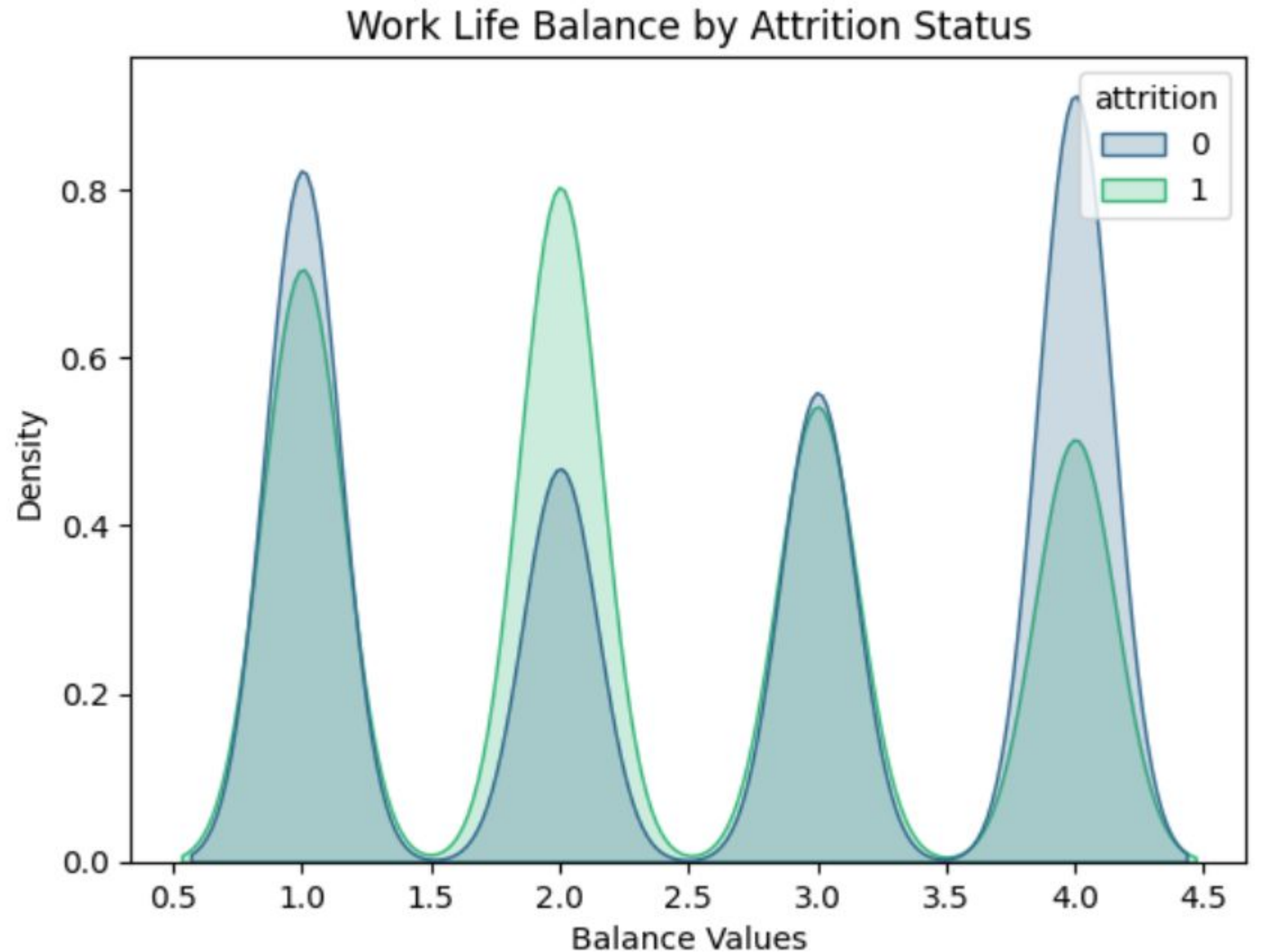
# Work Life Balance Impact

## WLB Values

- 1: Poor
- 2: Moderate
- 3: Good
- 4: Excellent

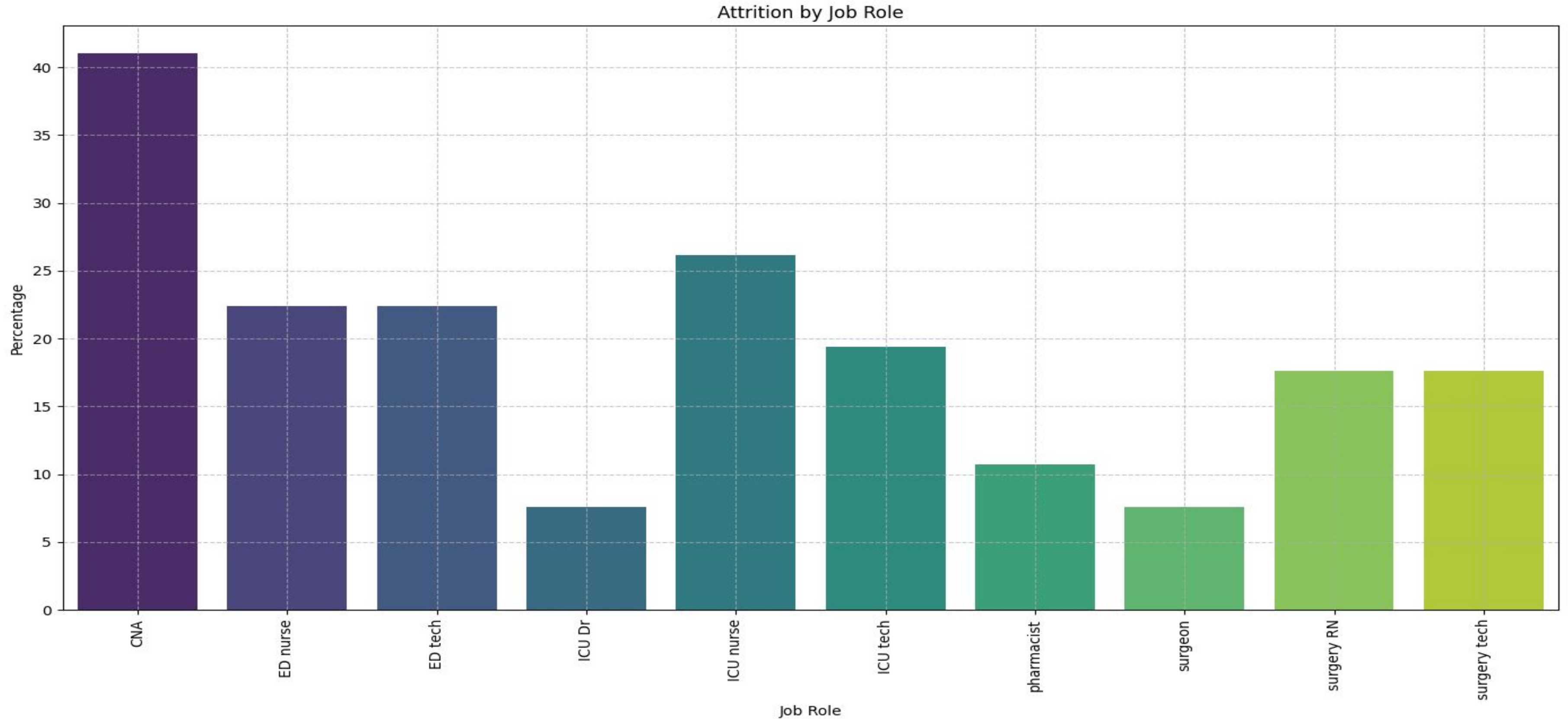
## Attrition Impact

- 1: 8% more likely
- 2: 12% more likely





# Attrition by Job role

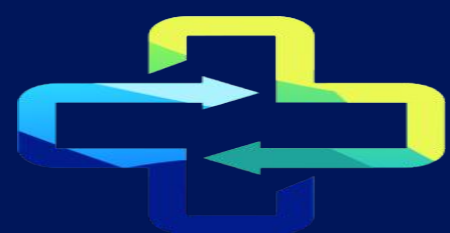
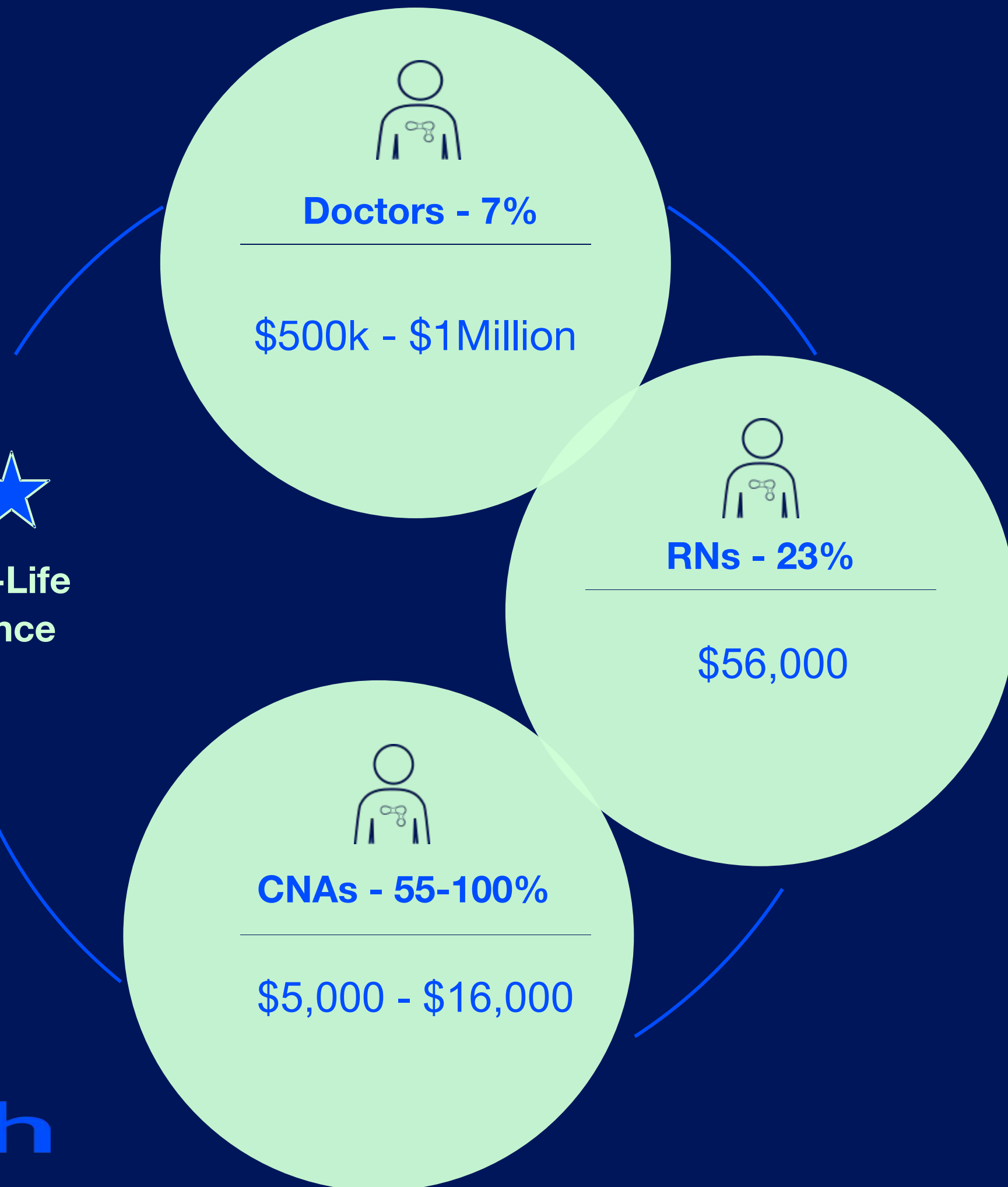


# Attrition Cost by Job Role

- Reducing MD attrition by .5% would save US hospitals \$250 - 500 billion dollars.
- For every 20 Travel Nurses eliminated, the average hospital could save \$2 Million Dollars per year.

## Recommendations:

- Nursing homes would benefit greatly from MedicalMatch's staffing solutions as they have the highest ratio of CNA's
- West, North-East and North-Central Regions have the highest Recruitment Difficulty Index. Those states would benefit greatly from the flexibility and work-life balance that MedicalMatch's platform facilitates



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source: NSi 2024 National Healthcare Retention & RN Staffing Report

# Classification Models Tested and Performance

Models tested: Bagging, RF, GBC, Adaboost, Dtree, XGBoost, Logistic Regression, ANN



Round 1:  
I ran each model  
w/out tuning to get  
baseline performance

As expected with an  
imbalanced dataset  
and no tuning



Round 2:  
Oversampling  
with SMOTE

Dtree and RF  
overfit on training  
and tanked on  
testing.



Round 3:  
Random  
Undersampling

Tree based  
models had  
Recall Scores  
of 72-75%



Round: 4  
Multiple ANNs  
w/dropout, Relu/Sig  
Adam

ANNs performed better out  
the gate with train/test  
performance 80-82%/

Thank you

Do you have any questions?



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