Conquering the Heights: Key Predictors of Success in Himalayan Mountaineering Expeditions*

Age, Team Size, Oxygen Use, and Prior Attempts Shape the Odds, While Higher Altitudes Diminish Success Rates

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This study examines the factors influencing the success of mountain climbing attempts by an expedition using a logistic regression model. More previous attempts, larger team size, and the use of supplemental oxygen were associated with higher success rates, while increased altitude and age reduced the likelihood of success. These findings improve our understanding of how personal, environmental, and logistical elements contribute to outcomes in high-altitude climbing. This knowledge can guide safer and more effective planning for future expeditions.

1 Introduction

Mountaineering has been growing as an activity since the 90s, the views and sense of challenge have brought people around the globe to summit more and more mountains every year. It is no surprise then, that when combined with a mountain range containing the highest above sea level peak in the world the Himalayas have had a rich documented history of mountaineering attempts. Mountaineering is a dangerous hobby however, with unpredictable weather and temperatures so high up it is natural that not all attempts to summit mountain peaks succeed here. This paper will find what factors have affected the climbers of the past to either conquer or be conquered.

This paper uses data sourced from Cookson (n.d.), based on The Himalayan Database (Salisbury, n.d.) about expeditions from 1905-2019 to analyze which factors help or deter climbers

*Code and data are available at: https://github.com/possibleburger2/.

from succeeding. We use a binomial logistic regression model to determine the probability of success based on a variety of demographic, enviromental, and organizational factors.

The estimand is the relationship between said factors and the success of a mountaineering expedition. By analyzing the data set, we can identify which factors contribute to a success or failure and by how much.

My analysis shows that Mountaineering is positively impacted by oxygen used, younger age, going in the fall and spring, and being a man while is is negatively impacted by the height of the mountain and the amount of people not hired in the expedition.

These findings practically inform climbers about the impact of good preparation and timing over personal factors like age and sex, showing that regardless of who you are, what you do is the biggest factor in succeeding in high-altitude mountaineering.

The paper is further organized into four sections. Section 2 discusses how the dataset used for the analysis was obtained and pre-processed. I will explain the variables of interest in the dataset used for the analysis. Section 3 describes the model being used for the analysis. Section 3.2 then highlights and discusses the trends and associations found during the analysis. Lastly, Section 4 talks about some interesting trends found in Section 3.2 in depth, linking it to the real world and also highlights the weaknesses and future of my analysis.

2 Data

The datasets were cleaned and analysed using the statistical programming software `R` (Team 2023) along with the help of `tidyverse` (CiteTidyverse, n.d.), `knitr` (CiteKnitr, n.d.), `ggplot2` (CiteGgplot, n.d.), `here` (CiteHere, n.d.), `dplyr` (CiteDplyr, n.d.), `rstanarm` (CiteRstanarm, n.d.), `arrow` (CiteArrow, n.d.) and `kableExtra` (CiteKableExtra, n.d.).

2.1 Overview

The raw datasets were obtained from Cookson (n.d.), who sourced them from The Himalayan Database (Salisbury, n.d.).

The Himalayan Database is a compilation of records for all expeditions that have climbed in the Nepal Himalaya. The database is based on the expedition archives of Elizabeth Hawley, a long-time journalist based in Kathmandu, and it is supplemented by information gathered from books, alpine journals and correspondence with Himalayan climbers.

The original database currently covers all expeditions from 1905 through Spring-Summer 2023 to the most significant mountaineering peaks in Nepal. Also included are expeditions to both sides of border peaks such as Everest, Cho Oyu, Makalu and Kangchenjunga as well as to some smaller border peaks. Data on expeditions to trekking peaks are included for early attempts, first ascents and major accidents. The updates to this database are published bi-annually.

My dataset, derived from Cookson (n.d.), contains the entries from 1905 through Spring 2019. There was not any widely available data for similar climbing data as extensive and detailed.

An expedition becomes an entry in my analysis data-set if, between 1905 and Spring 2019, there was an attempt to climb any one of the many Himalayan peaks in Nepal. This includes expeditions that were abandoned before the day of the climb due to poor planning or other issues.

The original data is split into 3 data sets: Peaks, Expeditions, and Members. Peaks is linked to the other two data sets by `peak_id` which is a unique code for each mountain peak. Peaks also contains more information about each specific mountain peak like `height_metres`, and first ascent year, country, and expedition id. `height_metres` is the height of the peak.

Members contains `member_id` which is a unique id for each individual in each expedition. Importantly it doesn't capture the same individual in different expeditions instead assigning two `member_ids`. It connects to Expeditions with `expeditions_id` and contains alot of information about the specific member during the expedition. Most importantly for this data we use average sex and age of all the members in each expeditions for the model.

Expeditions contains most of the important data for our model since the model determines the success rate of an expedition as opposed to an individual. The `year` column captures the numeric year of the expedition, and `season` indicates the season in which it occurred, such as "Autumn" or "Spring." The `termination_reason` column describes the outcome or reason for the expedition's conclusion, such as "Success (main peak)" or "Accident (death or serious injury)." Details about expedition composition are captured in `members`, which indicates the total number of members, and `hired_staff`, representing the count of additional staff hired. The `oxygen_used` column is a logical variable indicating whether supplemental oxygen was used, while `sex_ratio` and `average_age` provide insights into the gender composition and average age of expedition members, respectively. Additional success metrics include `success`, a logical column indicating whether the expedition achieved its goal, and `age_range`, a factor summarizing the age distribution of members. Finally, the data set includes `height_attempted`, a numeric column for the altitude reached during the expedition, and `previous_attempts`, representing the number of prior attempts made to climb the same peak.

2.2 Success

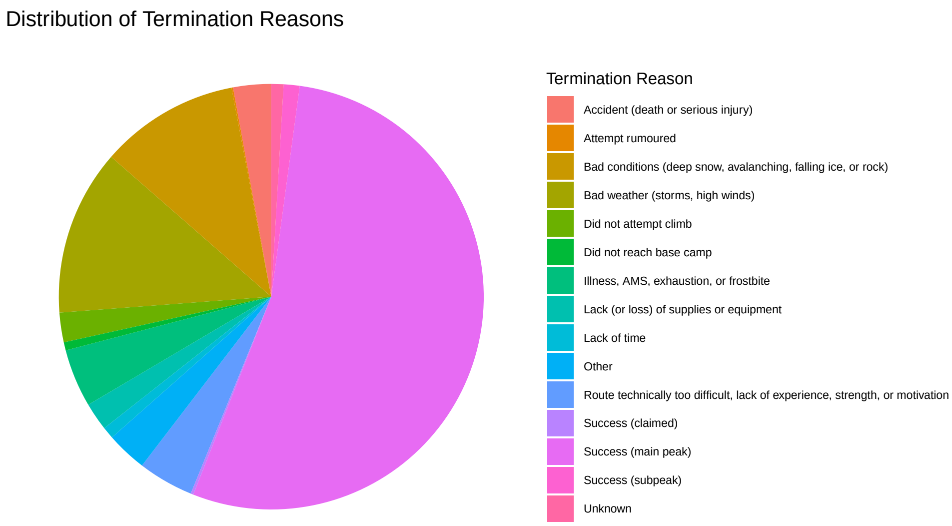

Figure 1: A slight majority of Expeditions succeed, with the most common reasons expeditions fail being enviromental issues

Figure 1 shows the distribution of termination reasons, which is the reason given for why the expedition failed.

"Success (main peak)", "Success (subpeak)", and "Success (claimed)" all count as successes for our modelling purpose. Sub peak successes are expeditions to a peak lower on the mountain but assuming the expedition planned to reach only the sub peak it should count as a success. There is an issue of a sub peak success not properly representing the attempted height of the peak but the relative infrequency of sub peak successes make it not a large problem.

Did not attempt climbs could have been removed from the data, however this is a valid issue the model should help predict so it was left it. The main issue is that there could have been many not attempted climbs left out of the data but we are not focusing on that outcome.

2.3 Expedition members

Members is the amount of non-paid people in the expedition.

Figure 2: Most expeditions have less than 3 members showing an exponetial decrease with an increase in members. The red lines indicate member amounts that have only had one expedition

Figure 2 shows most expeditions are parties of less than 3. All expeditions with missing data or with zero members were left out so the less than 3 bucket is not over represented. This distribution makes sense since larger parties require larger and larger amounts of effort and coordination.

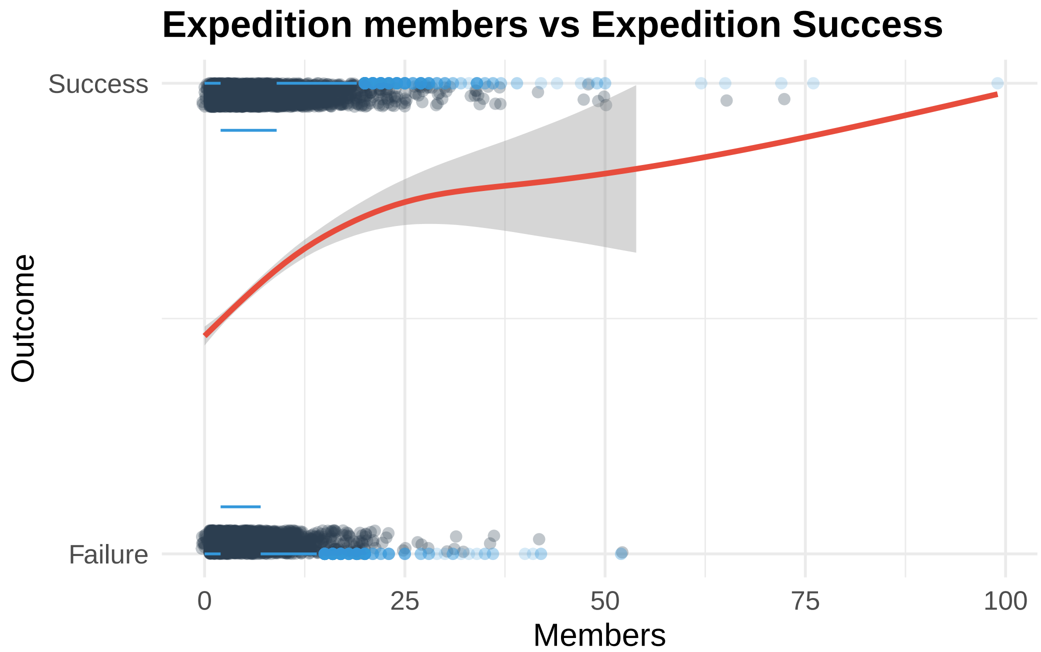

Figure 3: Party size vs Ex

Figure 3 shows a positive relationship between amount of members and expedition successes. The trend line also shows the confidence interval given by the grey area. As there are less data points with the increased members the less reliable the trend line is for this relationship. While there could be a negative relationship past 25 members, for most expeditions it shows that the more members the greater the chances of successes.

Hired staff

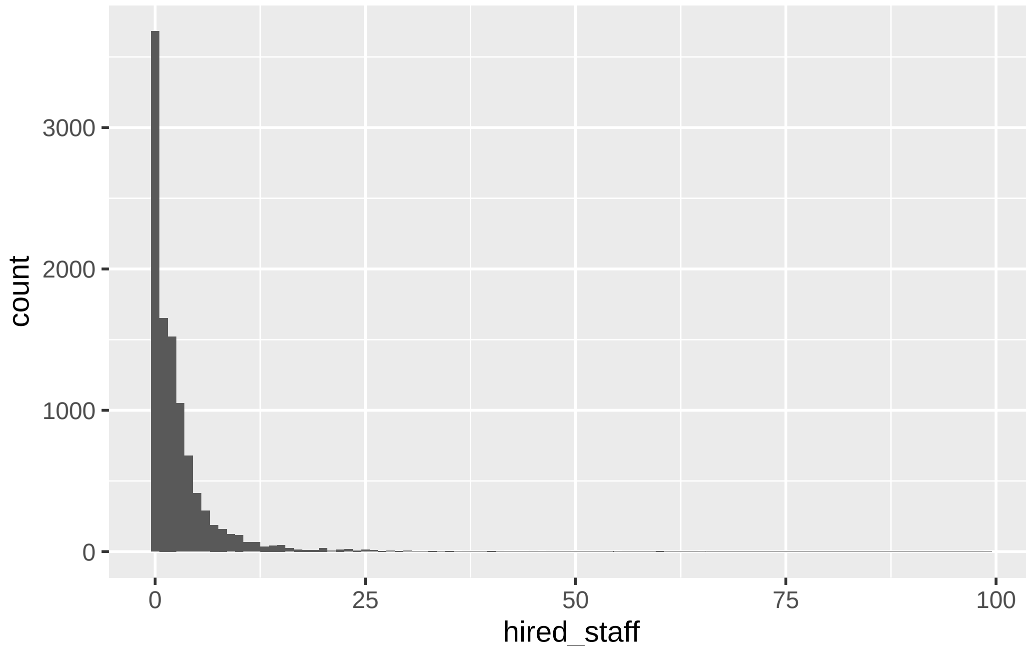

Figure 4: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

2.4 Season

2.5 Year

2.6 Average age of expedition

2.7 Proportion of women to men

can be because many of the data points are the same people, data could represent experience on success rather than gender composition

2.8 Height of mountain attempted

Figure 8 shows most peaks sit around 6000 meters above sea level, with a right skewed distribution and a maximum of almost 9000 meters and a minimum of 5250 meters.

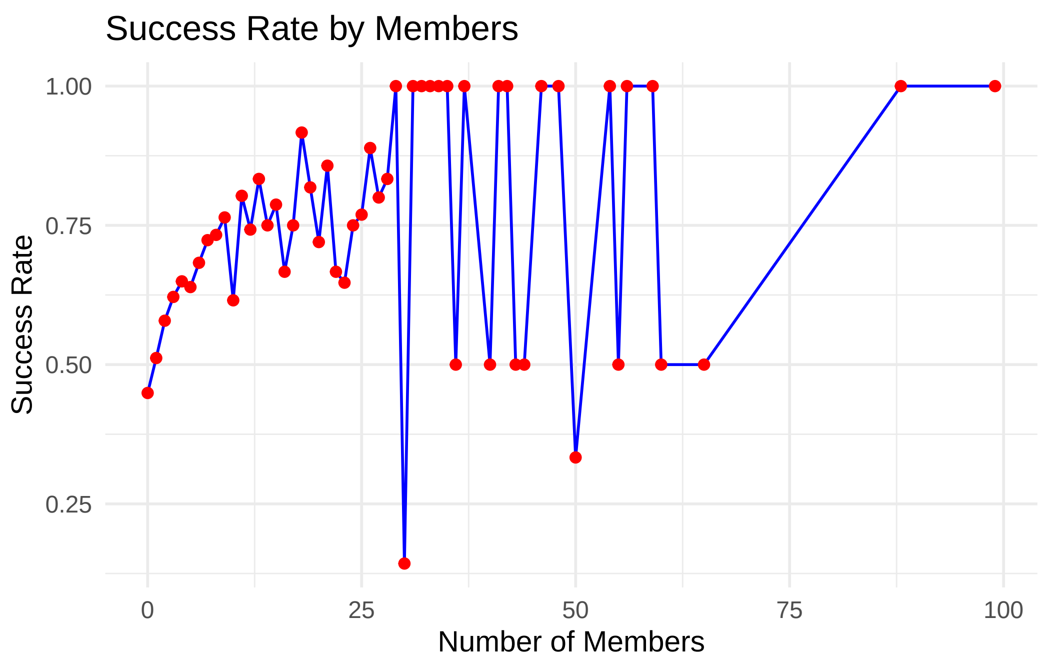

Figure 5: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

The Himalayan mountain range spans a large amount of distance, which means that the graphed distribution does not represent the distribution of ALL peaks in the Himalayas. Instead this distribution represents the distribution of peaks commonly attempted/climbed.The Himalayas starting at X M starting above 2000m sea level combined with the lowest height required to be considered a peak, the distribution starts at 5000m above sea level.

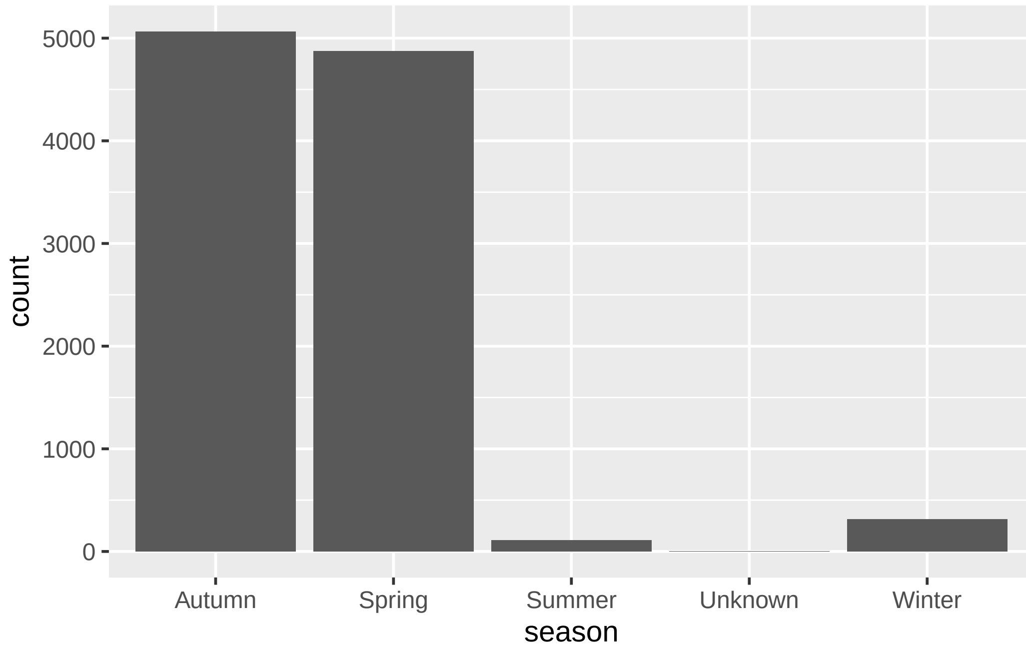

Figure 6: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

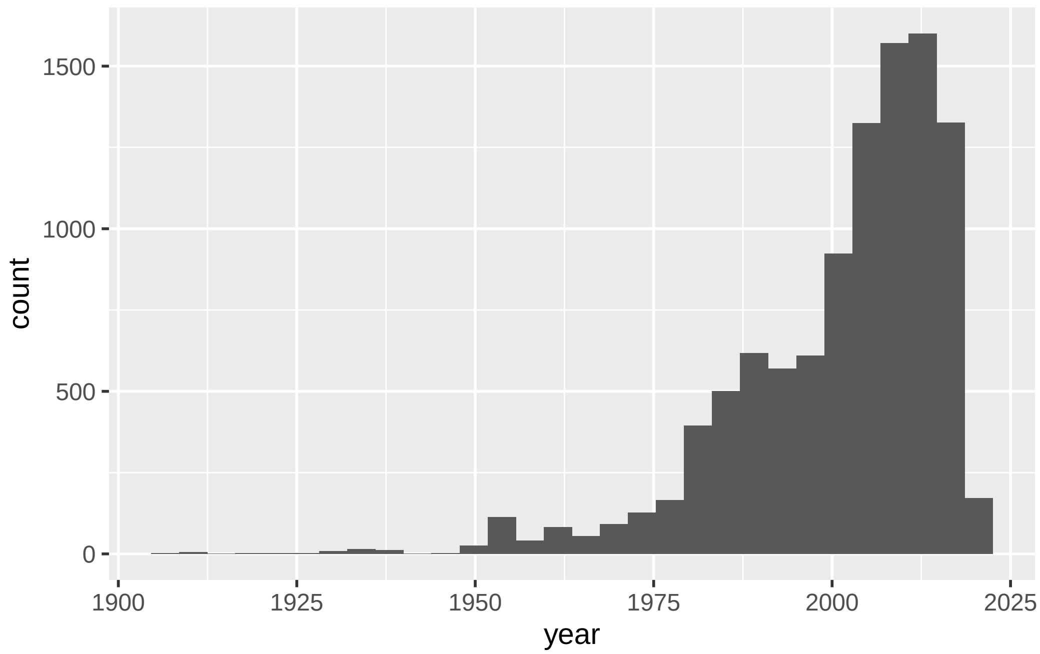

Figure 7: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

2.9 Climbing attempts

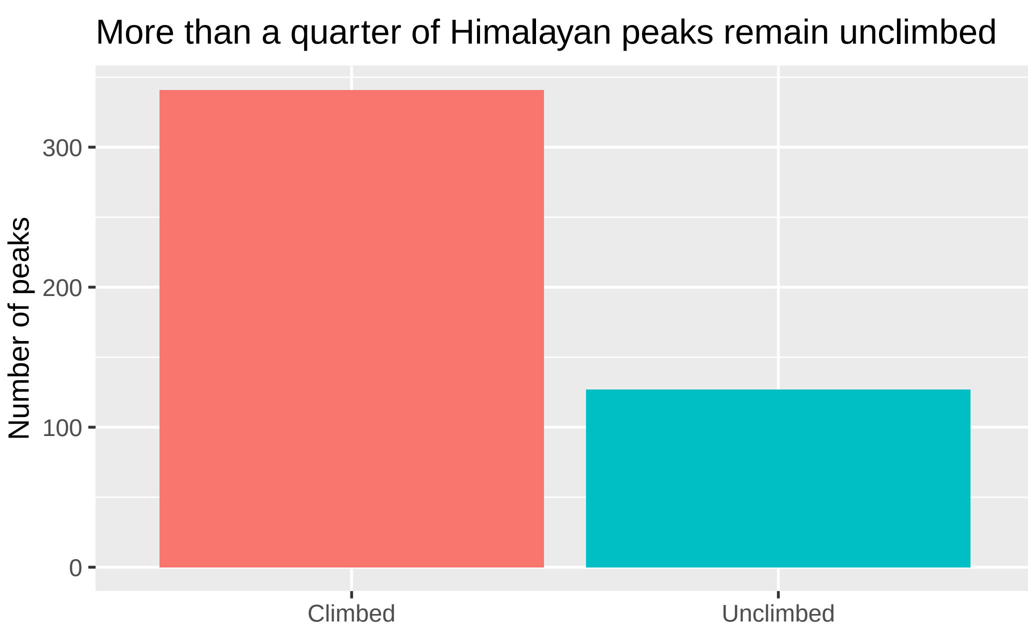

Figure 17: Amount of unclimbed Himalayan peaks

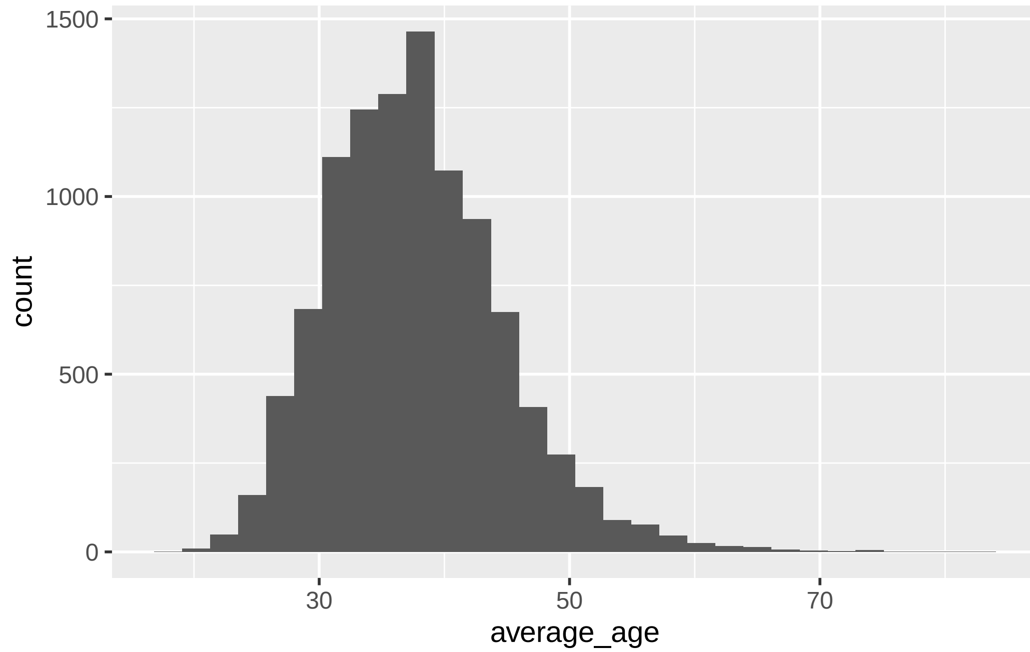

Figure 8: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

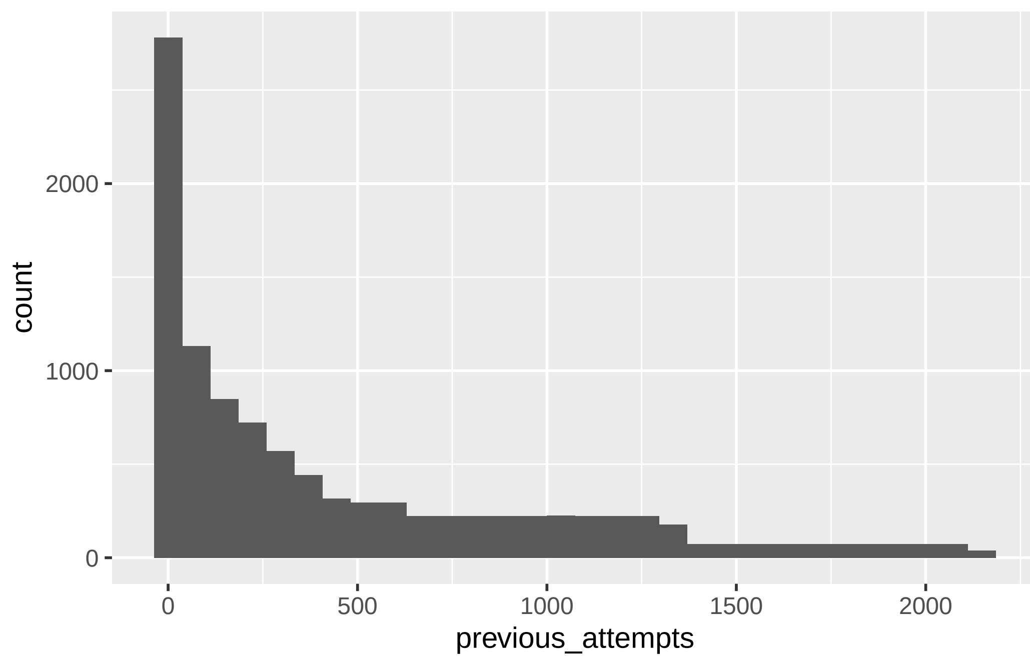

Figure 18: Amount of unclimbed Himalayan peaks

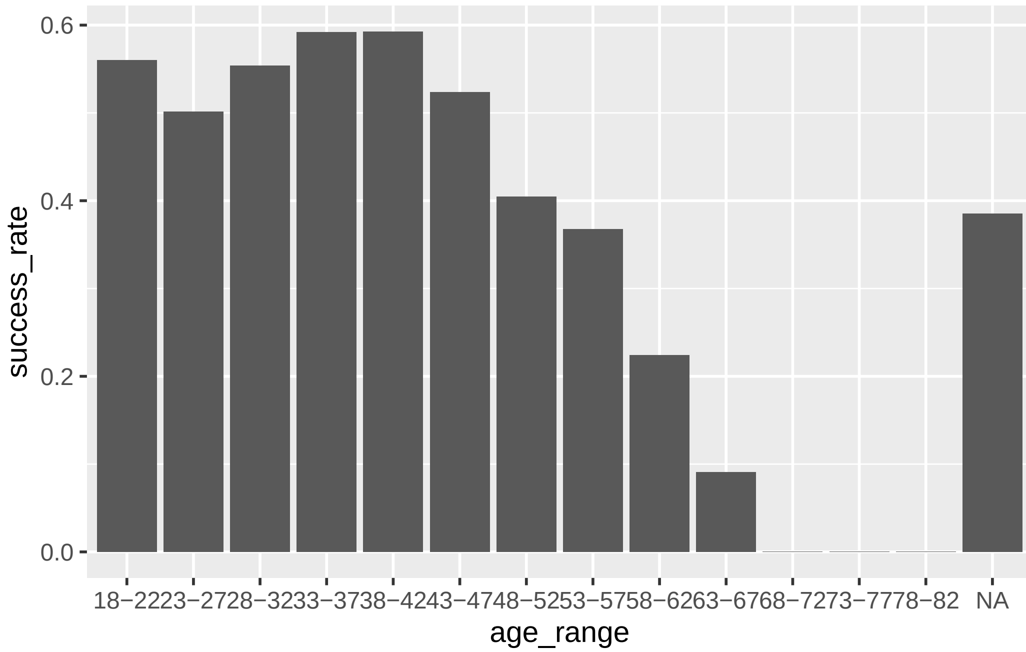

Figure 9: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

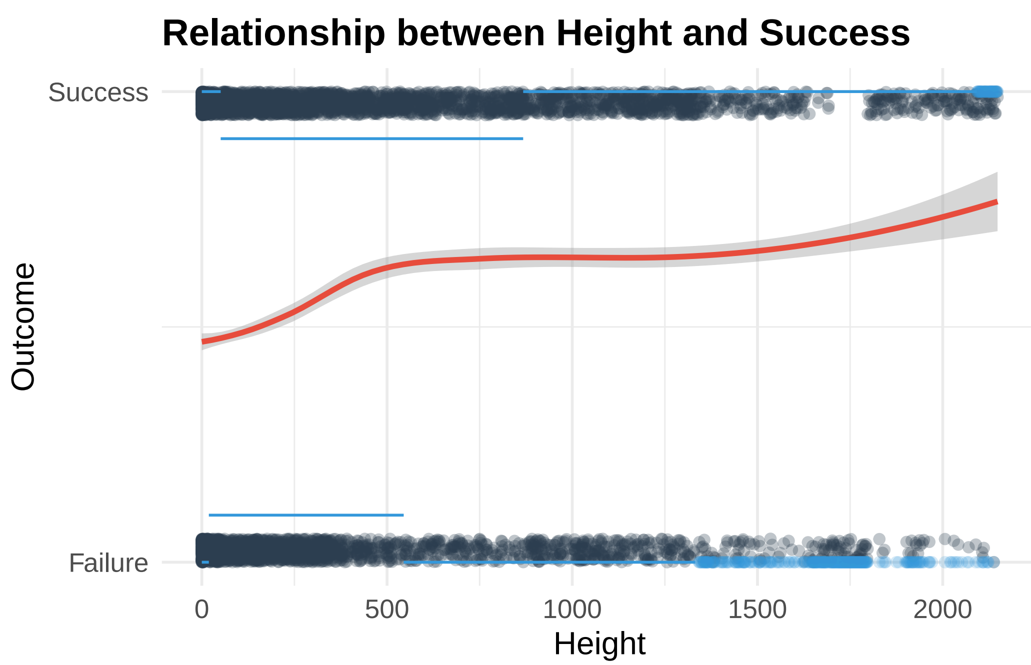

Figure 19: Amount of unclimbed Himalayan peaks

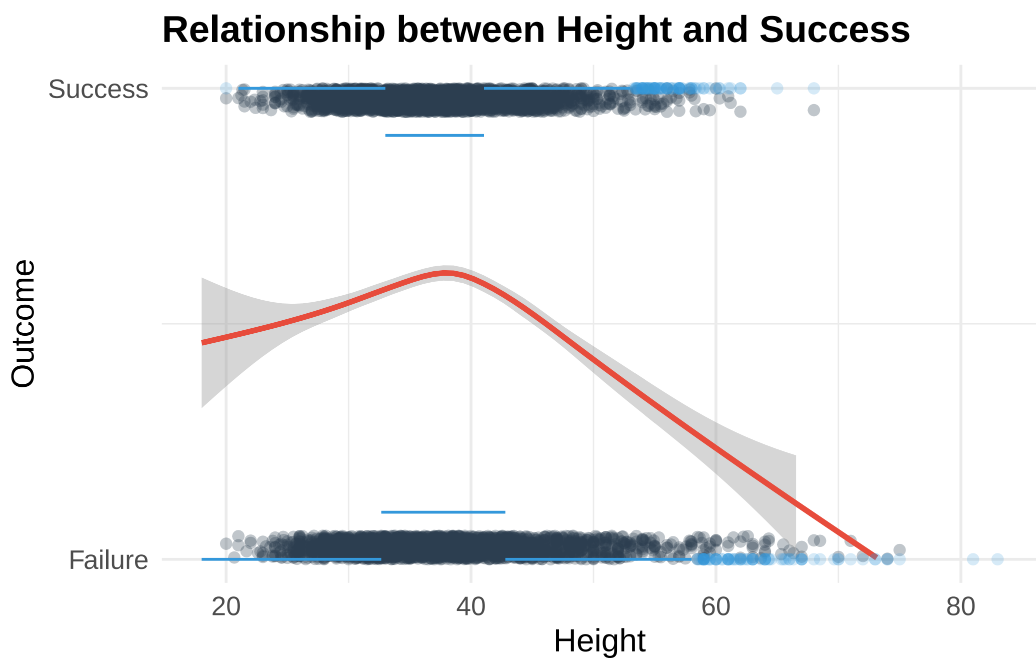

Figure 10: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

This graph shows that despite over 100 years of climbing history, not all attempted peaks have been conquered. Why do so many climbs fail however? The following graph shows the most common reasons.

2.10 Measurement

The measurement of Himalayan climbing data in the referenced dataset involves converting real-world phenomena—such as expeditions, summits, and fatalities—into structured entries. This process begins with records collected from expedition reports, which are typically submitted by climbers or organizations. These reports include details about expedition dates, routes, climbers' nationalities, success in reaching the summit, and any fatalities or injuries that occurred.

The dataset relies heavily on sources like The Himalayan Database, a comprehensive archive maintained by Elizabeth Hawley and her successors. This database aggregates information from direct interviews with climbers, expedition documentation, and third-party reports. However, the translation of these real-world events into dataset entries introduces several challenges. Discrepancies may arise due to incomplete or inconsistent reporting, varying definitions of a "summit," and the underrepresentation of smaller, independent expeditions.

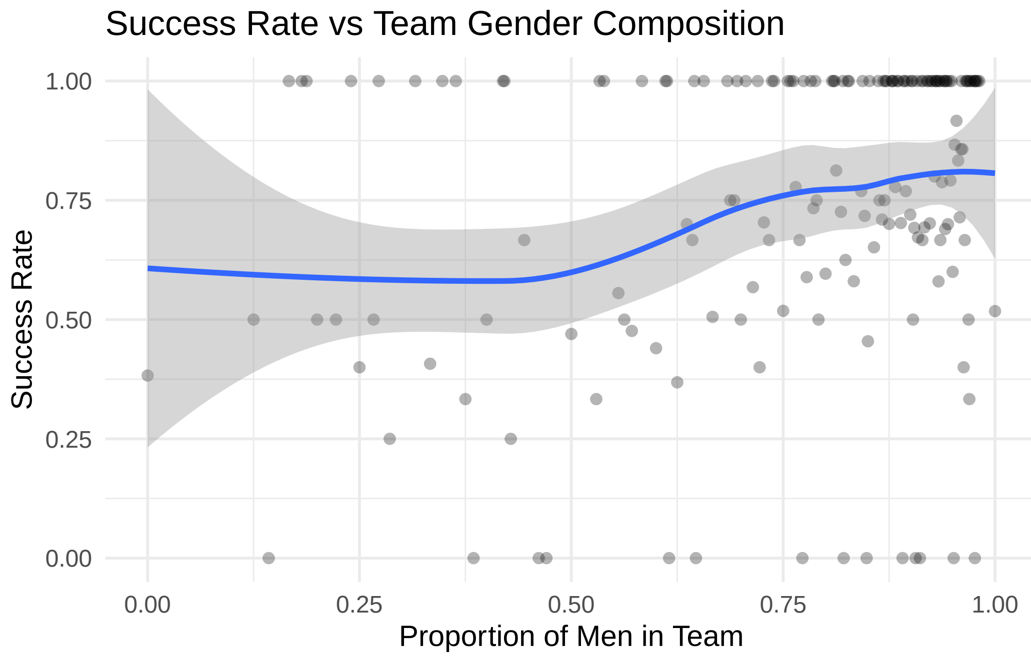

Figure 11: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

For example, an expedition is recorded in the dataset only if sufficient documentation is available to verify its occurrence and outcomes. Factors such as weather conditions, local incidents, or logistical difficulties that don't result in a summit or a fatality may not be consistently recorded. Additionally, subjective elements, like the climbers' or organizers' interpretation of success, influence the data's structure. These steps, while thorough, highlight potential biases in how phenomena are represented as measurable data.

3 Model

I used a Binary Logistic Regression uses the age of an individual,the amount of members in their expedition, the amount of oxygen they used, the season of their climb, their sex and the height of mountain to determine the likelihood of an individual of summit-ting the peak or "succeeding". A Binary Logistic Regression is a statistical method to predict binary outcomes like the success or failure of a climb based on both categorical and continuous variables. The Model uses six independent demographic variables: "age","members","oxygen_used","season","sex", and "height_metres" and the dependent variable is "success" The logistic regression model I

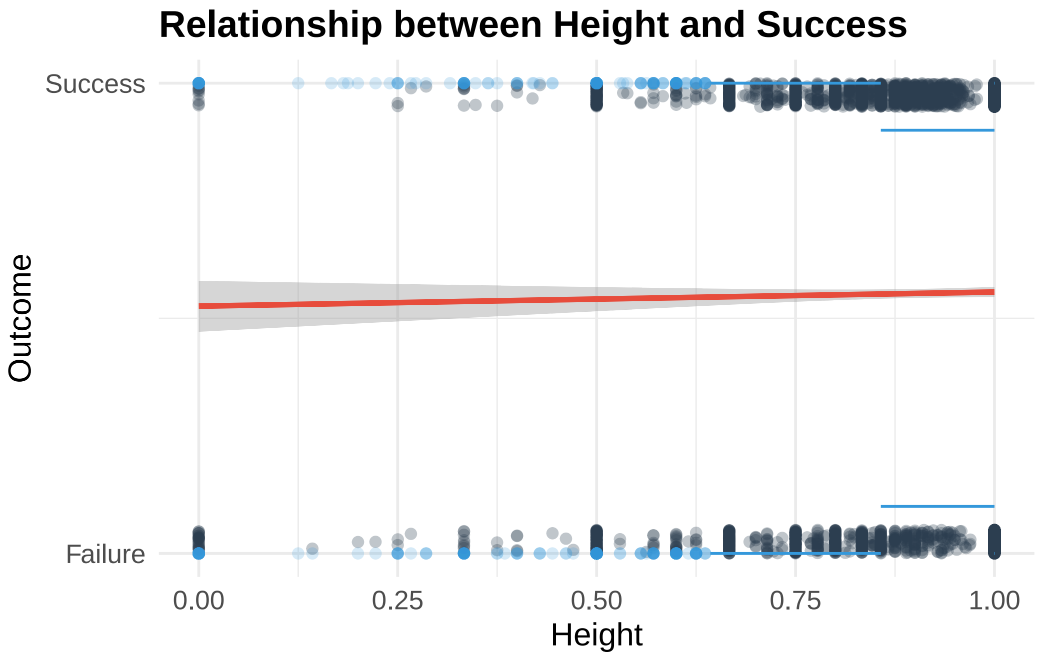

Figure 12: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

will be using is:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \beta_0 + \beta_1 \times \text{averageage} + \beta_2 \times \text{members} + \beta_3 \times \text{oxygenused} + \beta_4 \times \text{season} + \beta_5 \times \text{heightattempted} + \beta_6 \times \text{year}$$

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \beta_0 + \beta_1 \times \text{averageage} + \beta_2 \times \text{members} + \beta_3 \times \text{oxygenused} + \beta_4 \times \text{heightattempted} + \beta_5 \times \text{previousattempts}$$

3.1 Model Justification

Table 1

	(1)
(Intercept)	6.871
	(0.423)
average_age	−0.024
	(0.001)
members	0.029
	(0.013)
hired_staff	0.019
	(0.210)
oxygen_usedTRUE	2.028
	(<0.001)
seasonSpring	0.095
	(0.392)
seasonSummer	−0.142
	(0.775)
seasonWinter	−0.264
	(0.319)
height_attempted	−0.001
	(<0.001)
year	0.000
	(0.996)
previous_attempts	0.001
	(<0.001)
sex_ratio	−0.129
	(0.683)
Num.Obs.	2057
AIC	2475.2
BIC	2542.7
Log.Lik.	−1225.589
RMSE	0.45

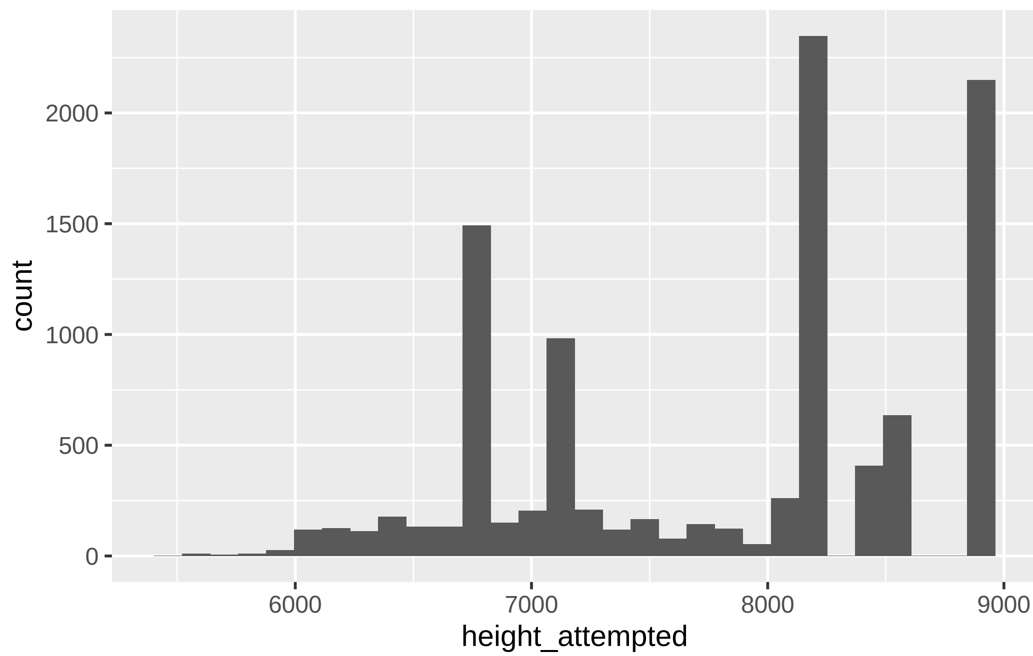

Figure 13: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

This table shows the influence (top number) and P-Value (bottom number in brackets) of each variable. For example each year increase in age reduces the probability they will succeed by around two percent with a P-value of 0.001 which means we are very sure of this relationship. A P-value of 0.001 means only 0.1% of the time this relationship can be explained by random chance. Because the standard level of uncertainty is less than 5% we should try to remove variables over a 0.05 P-value. There are also several figures relating to model accurary at the bottom of the figure;the main one to focus on is RMSE. An RMSE of 0.41 means the model predicts results within 41% of the actual results. For a model with a binary outcome it means our model predicts successes 59% of the time.(removed entries for each country due to formatting issues)

Because we have so many statistically insignificant variables at a 5% uncertainty we should try to remove them to see the impact it has on the model

Table 2

	(1)
(Intercept)	6.571
	(<0.001)
average_age	−0.023
	(<0.001)
members	0.036
	(<0.001)
oxygen_usedTRUE	2.093
	(<0.001)
height_attempted	−0.001
	(<0.001)
previous_attempts	0.001
	(<0.001)
Num.Obs.	2057
AIC	2467.3
BIC	2501.1
Log.Lik.	−1227.650
RMSE	0.45

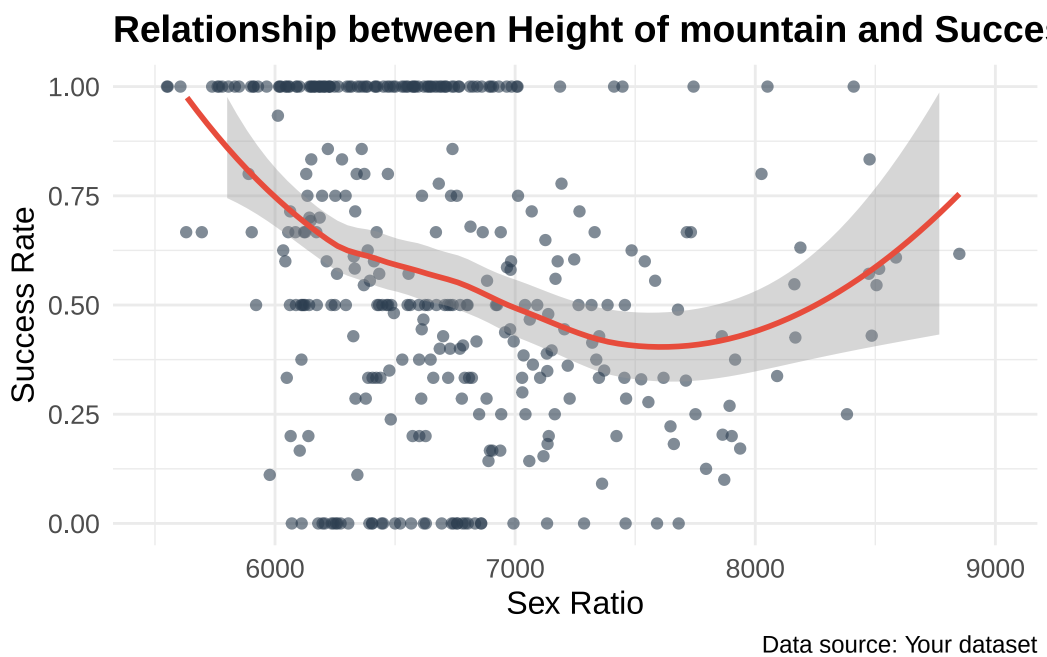

Figure 14: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

The second table shows the results when citizenship and hired_staff are removed. We see the RMSE only grains 0.01, meaning it loses 1% accuracy. This means the citizenship of climber nor the amount of hired staff did not contribute to the model's accuracy and were good to remove.

Table 3: ANOVA Model Comparison

Resid. Df	Resid. Dev	Df	Deviance	Pr(>Chi)
2045	2451.177	NA	NA	NA
2051	2455.301	-6	-4.123818	0.6599248

This anova table just confirms that there is no difference in the modelling ability after removing the two predictor variables.

3.2 Results

```
         Actual
Predicted FALSE TRUE
        0   526  266
        1   417  847
```

```
[1] "Accuracy: 0.667801556420233"
```



```
[1] "AUC: 0.725339880845193"
```

Figure 21 shows most of the coefficients do not have a large affect on success however have a very certain affect on success. The season you go are all relative to fall, so going during the fall has a large measured impact on success as well as oxygen used and sex.

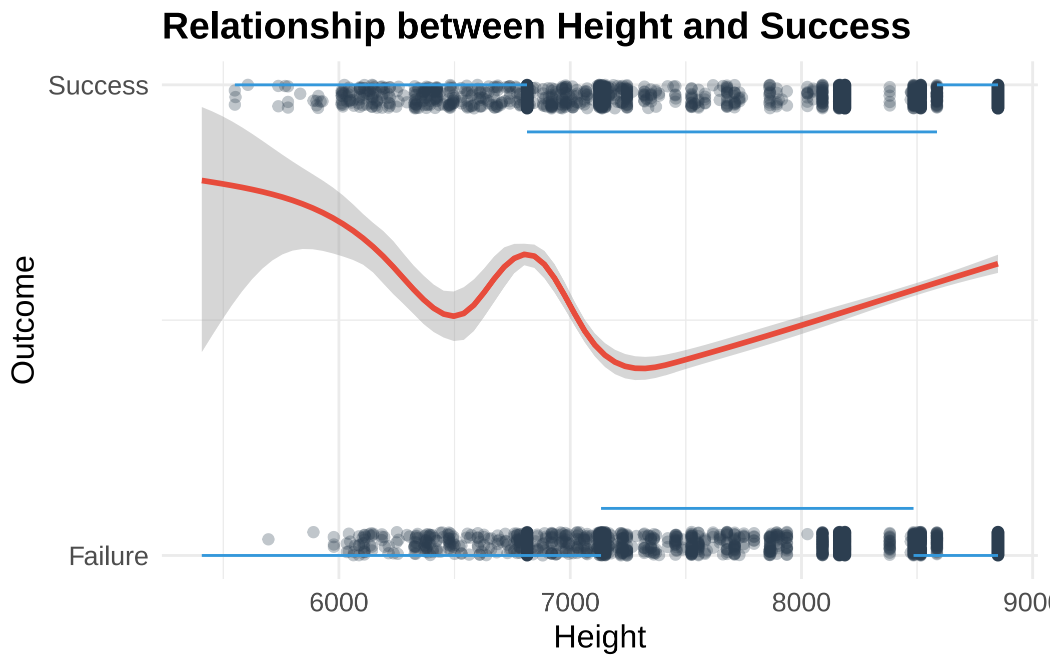

Figure 15: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

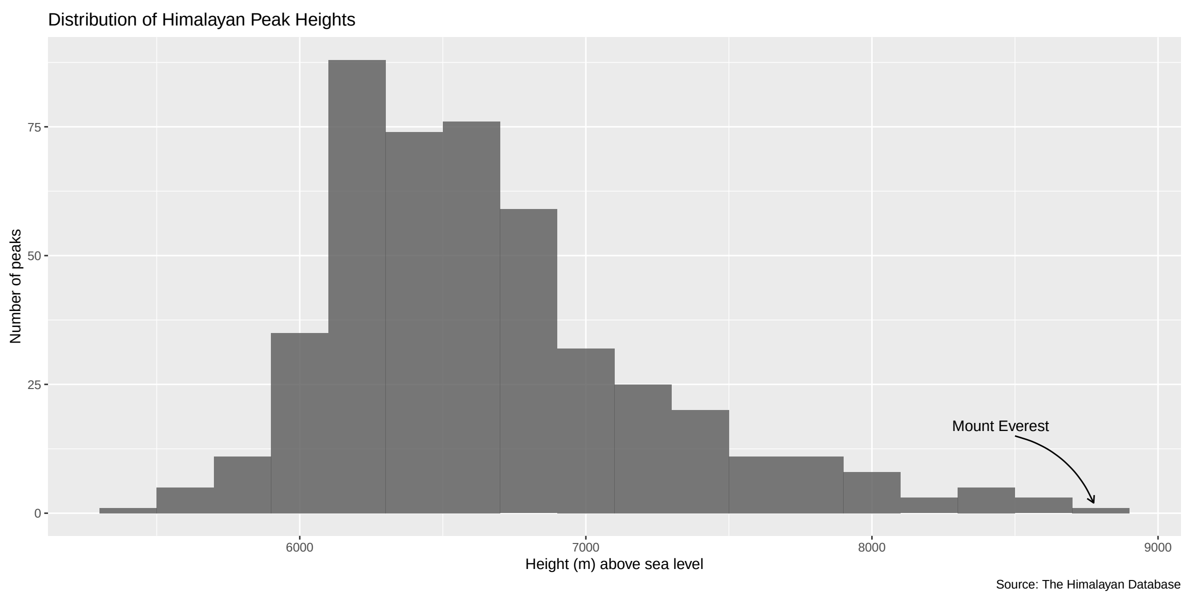

Figure 16: Distribution of Himialayan peaks, mountains recorded are centered around 6200 M above sea level..

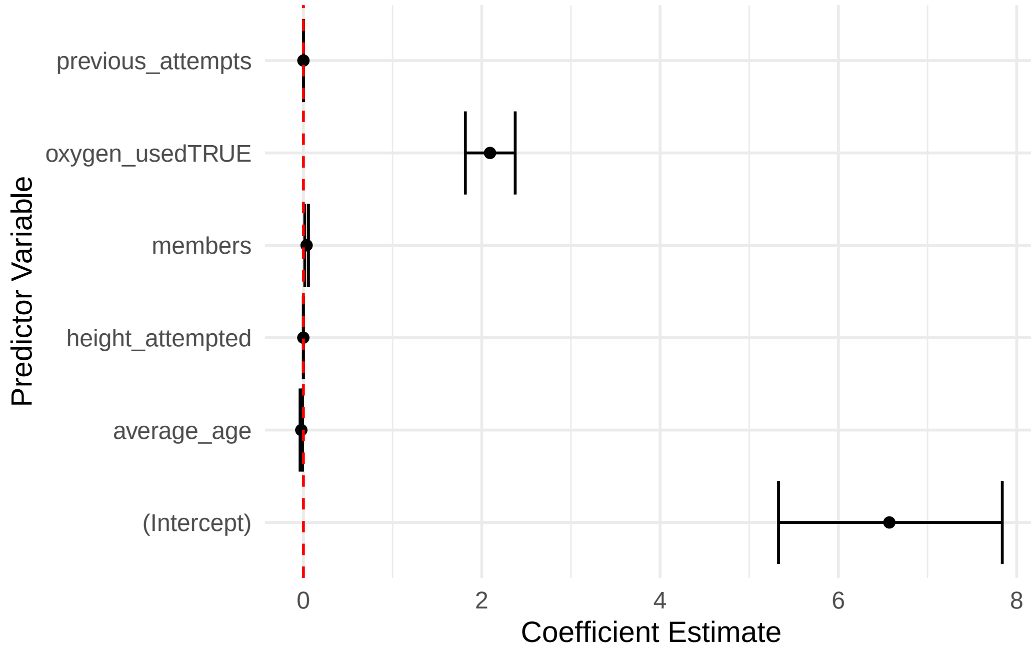

Figure 20: Coefficients of the model

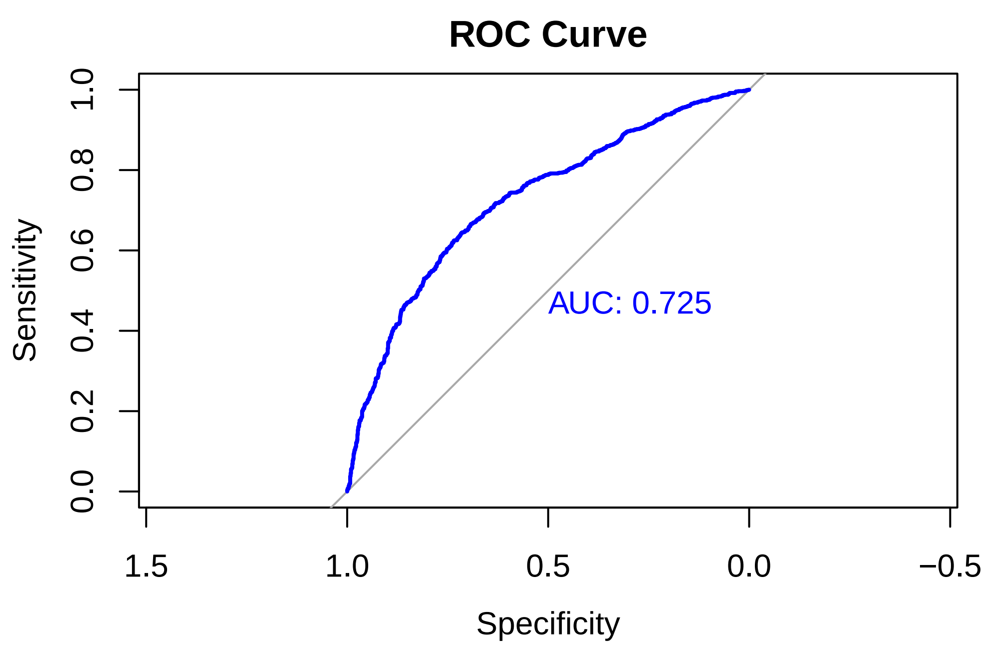

Figure 21: Coefficients of the model

Oxygen usage reflects prepardness, technological advancement, climbing community collective experience/coordination

While season data was deemed unimportant for the model, if you look at the season distribution of climbing it is obvious that climbers prefer spring and fall. This is due to the more predictable calmer weather.

Sex ratio

Previous attempt data

This data and the following data analysis mostly covers the human part of the risk in mountaineering. That is to say it does not take into account the many environmental factors that exist that cause expeditions to fail.

What can be done about this: Firstly weather forecasting data should be considered for success rate since it constitutes a quarter of all expedition failures.

Other factors like avalanche risk can be measured by snow depth, recent weather patterns, combined with weather forcast data. This should prove to be more difficult to predict than overall weather affects since it is very dependent on the specific geography of the peak.

This is similarly rock and ice risk can be measured by weather/erosion patterns, analysis of geography. This would be very difficult to realistically observe.

We should also look to observe individual health issues/risks as well as individual skill/ climbing history to more accurately predict success.

While peak height is a valuable way to determine peak difficulty there are a variety of other factors about the geography of a climb that can make it easier or more diffucult.

In general mountaineering carries some sort of risk and that is part of the appeal. As technology and experience decreases risk people will attempt riskier routes and peaks.

4.1 Nature of Mountaineering

4.2 What was done

4.3 What was learned

4.4 Missing data

4.5 Going forward

4.6 Chances of success decline with increase in age

Age is a significant factor in mountaineering success, with success rates generally decreasing as climbers get older. This decline can be attributed to various age-related factors, such as the natural loss of muscle mass, strength, and aerobic capacity. As climbers age, they may also experience reduced agility, flexibility, and slower recovery, which can hinder their performance on difficult terrain and in recovering from intense physical exertion.

In addition to these physical challenges, older climbers may face health issues like cardiovascular problems, joint stiffness, and decreased bone density, all of which can further limit their ability to meet the physical demands of mountaineering. These factors contribute to a reduced ability to handle the stresses of expeditions and increase the likelihood of difficulties along the way.

However, it is important to recognize that success in mountaineering is not solely determined by physical ability. Experience, skill, preparation, and mental strength play crucial roles in overcoming the challenges of the climb. Older climbers, despite the physiological decline that comes with age, can still achieve success by leveraging their experience, using strategic planning, and maintaining a strong mindset. These factors enable them to adapt to the challenges they face, showing that age does not necessarily preclude achieving mountaineering goals.

In summary, age-related impacts on mountaineering success are significant, with success rates generally decreasing as climbers age. However, older climbers can overcome some of these challenges through experience, skill, strength training, and a strong mindset, allowing them to continue enjoying mountaineering well into their later years.

4.7 Weaknesses and Limitations

While my analysis offers valuable insights into the factors influencing a successful summit, it is important to acknowledge the weaknesses and limitations.

In summary, while age can impact mountaineering success, older climbers can still achieve summit success through a combination of experience, skill, and mental strength.

The analysis conducted has some limitations that need to be addressed. One of the main weaknesses is that the success probabilities may be skewed due to inaccuracies in the data. For example, the number of solo ascents in the dataset is much smaller than the number of group ascents, yet the model suggests that solo ascents have higher success rates. This could lead to a misconception that solo climbs are more successful, without considering other contributing factors such as the determination and willpower of those opting for solo expeditions. These climbers might be more motivated, which could be a confounding factor influencing their success rates. The dataset also has some inconsistencies, especially in variables like nationality and group size. Inconsistent reporting methods between different countries, such as the way group size is recorded in Nepal versus China, led to these factors being removed from the analysis. This inconsistency limits the ability to draw conclusions based on these variables.

Additionally some variables were not readily available in the data set that would have a large influence on the findings. Factors like individual skill, mental direction, and external factors like difficulty of the climb are not included or well represented in the data. ## Future Directions Looking ahead, future research should focus on improving the dataset by exploring additional factors that could influence summit success. One such factor is the number of attempts made by a climber. Understanding whether repeated attempts increase the likelihood of success or if there is a point of diminishing returns could provide valuable insights into the role of perseverance and learning from past experiences. Additionally, examining the level of technical skill or experience of climbers could help determine if those with more specialized training or knowledge are more likely to succeed. A deeper understanding of the climbers' preparedness—both physically and mentally—would also be crucial. This could include factors like training regimes, mental resilience, and coping strategies, all of which may play a critical role in a climber's ability to reach the summit. Lastly, studying the support systems available to climbers, such as the role of guides, sherpas, or expedition teams, could reveal how these resources impact success rates. By considering these factors, future research can provide a more comprehensive understanding of what contributes to successful mountaineering expeditions.

A Appendix

A.1 Cleaning

For the analysis data, the cleaning steps were from Cookson (n.d.)

The data cleaning process described in the provided script involves transforming raw data into a more consistent, accurate, and analysis-ready format. The first step in the cleaning process is applied to the peaks dataset, which contains information about various mountain peaks. In this step, columns are renamed for clarity, such as changing PEAKID to peakid and PKNAME to peakname. Only the necessary columns are retained, while others are discarded to simplify the dataset. A key aspect of this cleaning is handling the climbingstatus column. The raw data uses numerical values (0, 1, 2) to represent the climbing status, so these numbers are recoded into meaningful labels like "Unknown," "Unclimbed," and "Climbed." Additionally, a data entry error is corrected for Sharpu II (identified by peakid == "SPH2"), where the year of the first ascent is changed to 2018 to fix an obvious mistake.

The second dataset cleaned is the expeditions dataset, which tracks various climbing expeditions. Here, the dataset is joined with the peaks dataset to bring in the peakname for each expedition using the peakid. Only the relevant columns are selected and renamed for clarity. The highpointmetres column is adjusted by setting any value of 0 to NA, as it likely indicates missing data. Categorical variables like terminationreason and season are recoded to make them more readable. The terminationreason column is recoded from numeric values (such as 0, 1, and 2) into descriptive labels like "Success (main peak)," "Bad weather," and "Accident." Similarly, the season column is recoded from numbers (0-4) into readable season names like "Spring," "Summer," "Autumn," and "Winter."

The third dataset, members, contains information about individual climbers. This dataset is also joined with the peaks dataset to associate each climber's expedition with the corresponding peak name. As with the other datasets, only the relevant columns are retained and renamed. Any value of 0 in the age column is treated as missing data and changed to NA. The deathcause and injurytype columns, which are initially represented by numeric values (0-12), are recoded into readable categories like "AMS" (Acute Mountain Sickness) and "Exhaustion." The cleaning also involves handling information related to deaths and injuries. For climbers who have died, the deathcause and deathheightmetres are updated, and similarly, the injurytype and injuryheightmetres are updated for injured climbers.

A.2 Observational data

Himalayan climbing data, particularly concerning summits and fatalities on peaks like Mount Everest, may misrepresent actual outcomes due to several factors, including incomplete reporting, commercial biases, and evolving definitions of success. These discrepancies can create a skewed understanding of the risks and achievements in high-altitude mountaineering. Incomplete Reporting

Many summits, fatalities, and near-misses in the Himalayas go unreported or inaccurately documented due to the remote and challenging environments of the region. Smaller expeditions, particularly those from less prominent countries or by independent climbers, may not submit detailed records. Additionally, incidents on less-frequented peaks are less likely to be covered in international or even regional climbing databases, leading to underrepresentation in global statistics. For example, organizations like the Himalayan Database, while comprehensive, rely heavily on self-reported data, which can vary in reliability depending on the source. Commercial Influences

The rise of commercial expedition companies has significantly influenced how climbing data is presented. For marketing purposes, these companies may highlight success rates while downplaying or omitting fatalities or unsuccessful attempts. Moreover, certain deaths that occur before or after the official climbing season might not be included in annual tallies, further skewing statistics. High-profile peaks like Everest often see overrepresentation in the data, as their fame and accessibility make them more frequently reported than other Himalayan mountains.

The definition of a “summit” itself can vary, adding further complications. On Everest, for example, some climbers might claim summits upon reaching the South Summit or other points close to the highest peak, particularly in cases of bad weather or emergencies. Such claims are sometimes accepted without verification, leading to inflated success statistics. Disputes over what constitutes a legitimate ascent, particularly as aided by modern technology like oxygen tanks and fixed ropes, also muddy the waters of accurate representation. Bias in Reporting Fatalities

Fatality rates may also be misrepresented due to a focus on high-profile accidents involving Western climbers or commercial expeditions, while incidents involving Sherpas and local climbers are often underreported. Sherpas, who take on the riskiest roles during climbs, such as route preparation and heavy load carrying, face disproportionate risks that may not be fully reflected in the data. Conclusion

The misrepresentation of Himalayan climbing data has implications for understanding the true risks and challenges of high-altitude mountaineering. Efforts to improve the accuracy of this data, such as independent verification and more comprehensive reporting systems, are essential for providing climbers, researchers, and policymakers with reliable information. Sources like The Himalayan Database (Salisbury, n.d.), the American Alpine Journal, and recent academic studies on mountaineering ethics and statistics provide valuable insights but also highlight the need for more transparent and standardized data collection practices.

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