Predicting customer churn at Health First

Data analysis, interpretation and prediction

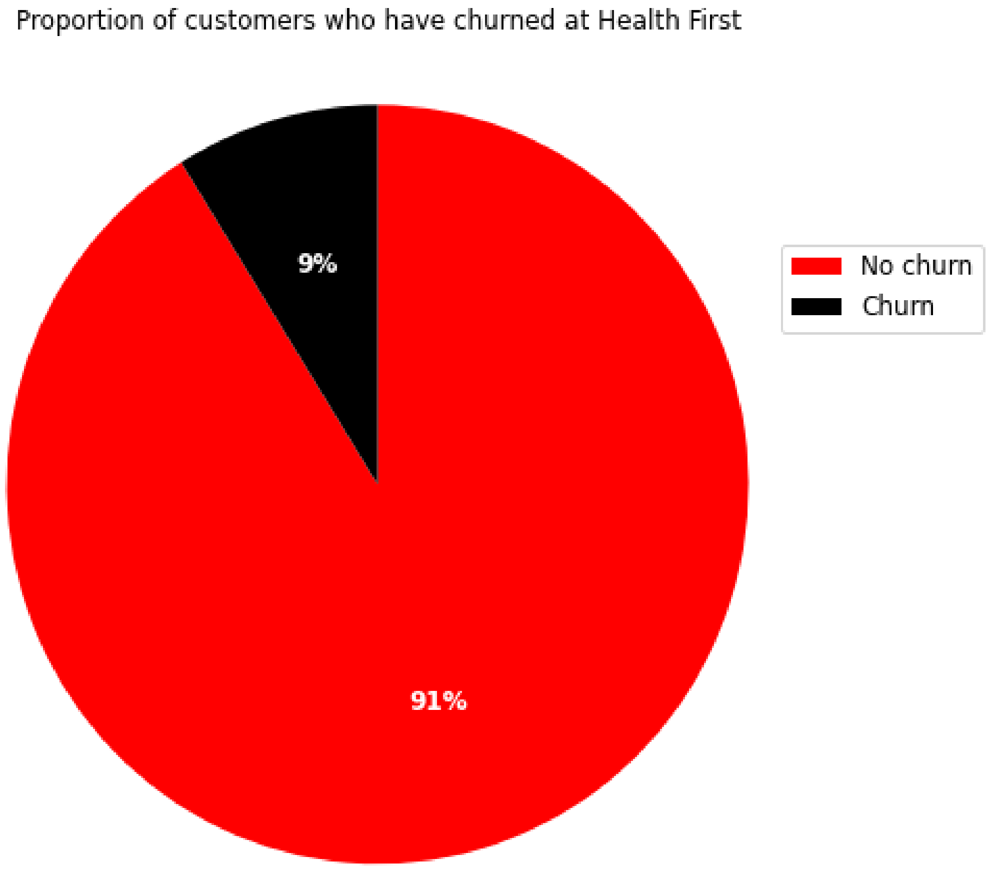
by Amy Birdee

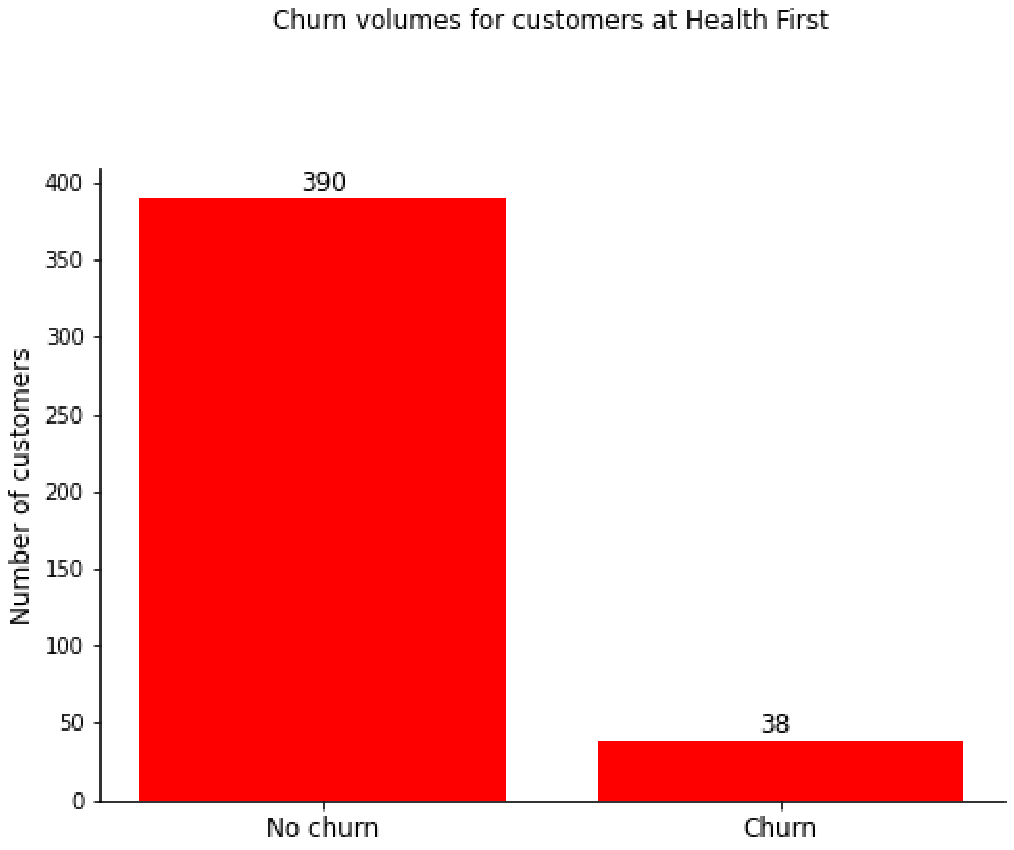
Introduction

- The data consist of details of customers at Health First, a hypothetical company focussed on improving the health of the nation
- Included in the data are variables such as the customer’s gender, what motivated them to improve their health, what their biggest challenges are and whether or not they churned during a six week period
- For ten customers, the churn data are blank
- This project aims to segment the customer data and build a classifier model which will predict whether or not those ten customers will churn
- The main findings in the data have been presented in graphical format and the data analysis has been carried out in Python
- The predictions have been made using a logistic regression model

How many customers churned at Health First?

- Churn rates after six weeks are very low at just **9%** which equates to only 38 customers

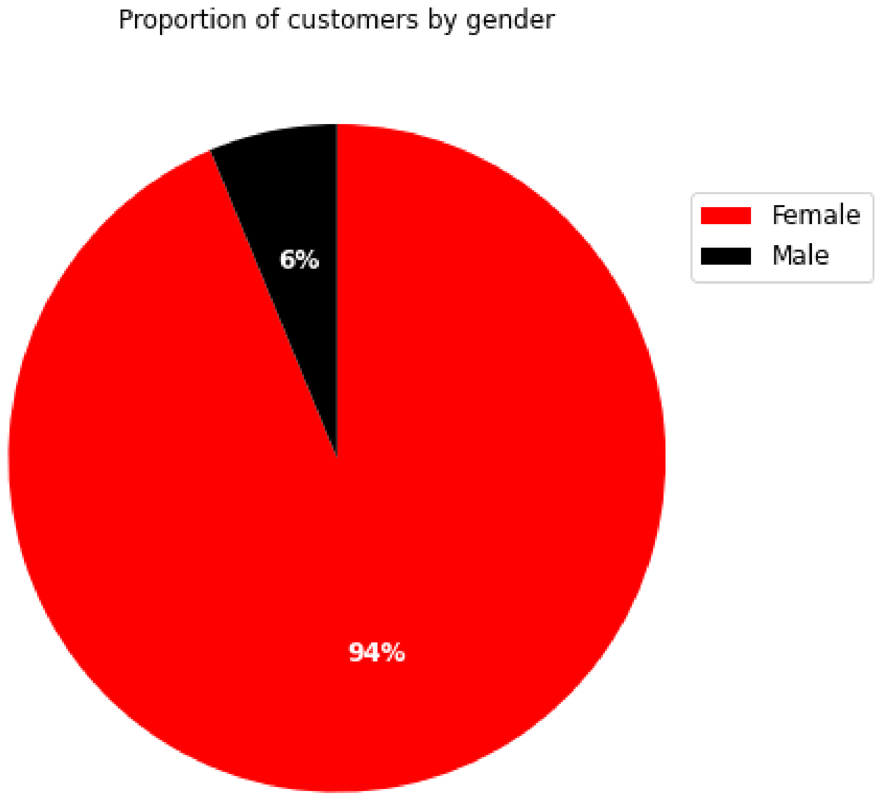


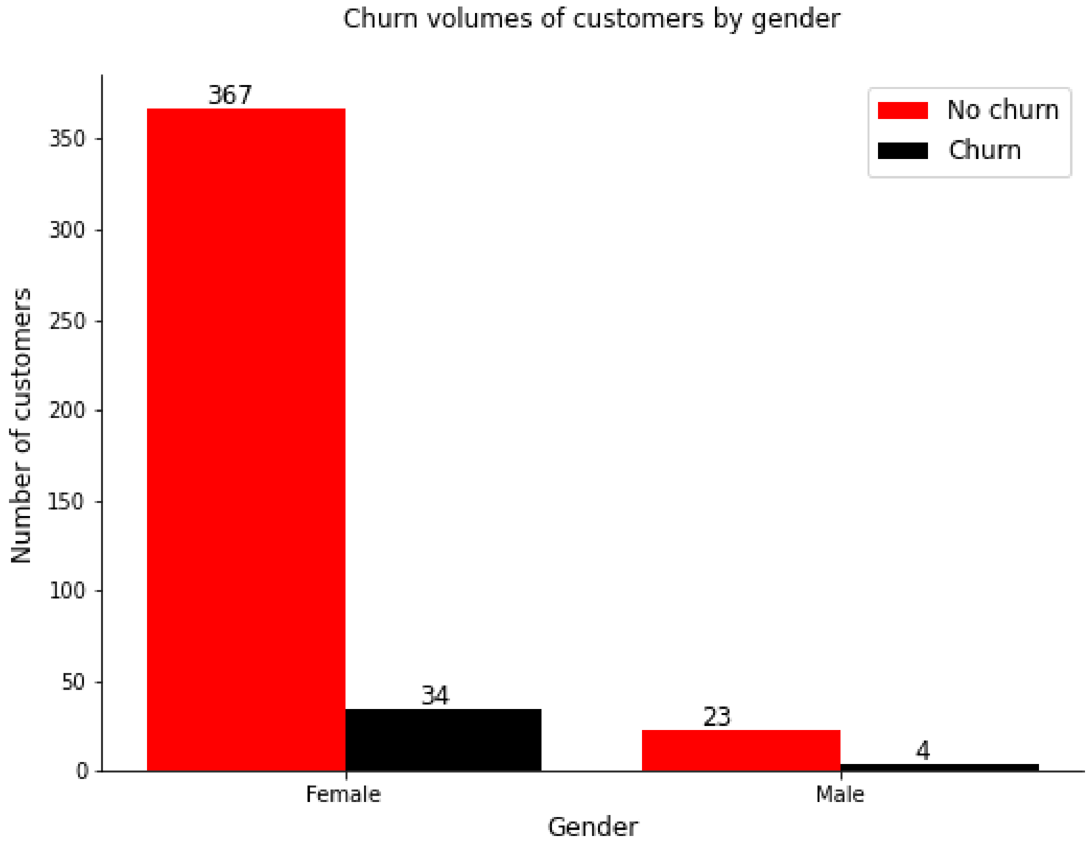


390 customers remained loyal to their new health regime

How does gender affect churn at Health First?

- The customer base is mainly made up of females – **94%** of customers are female

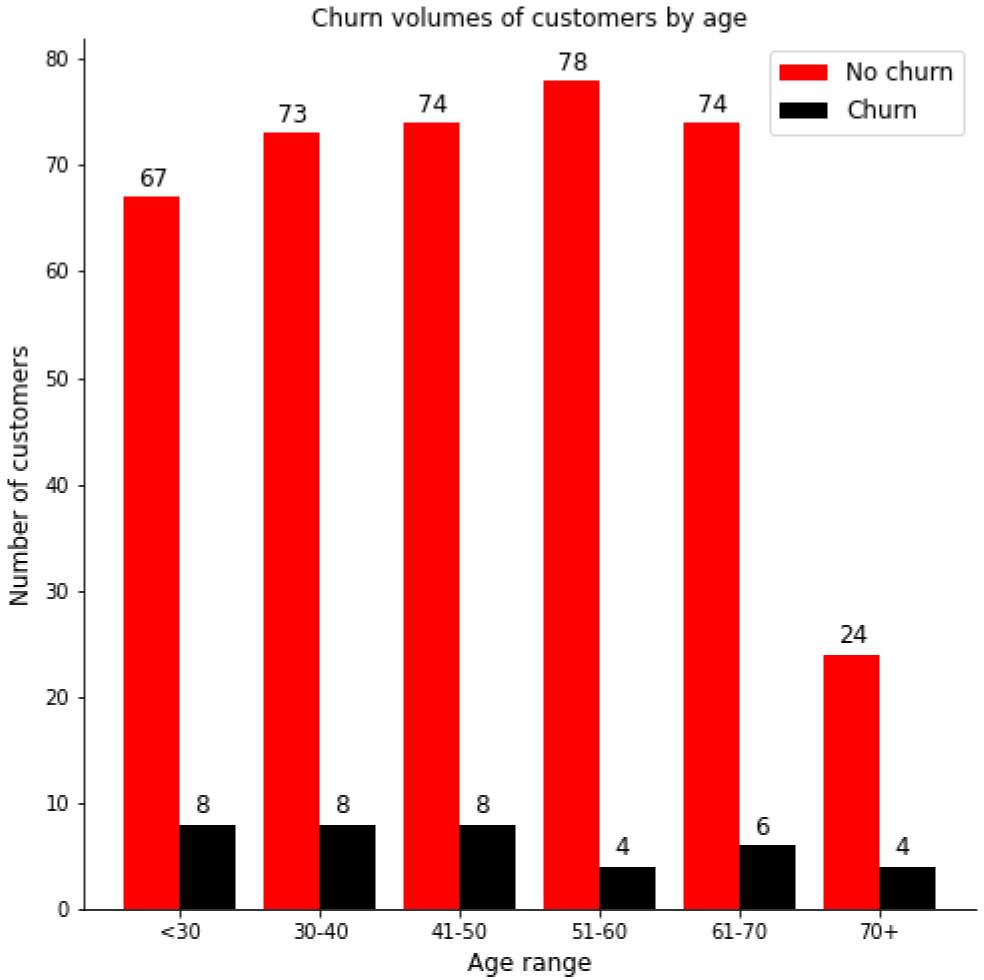


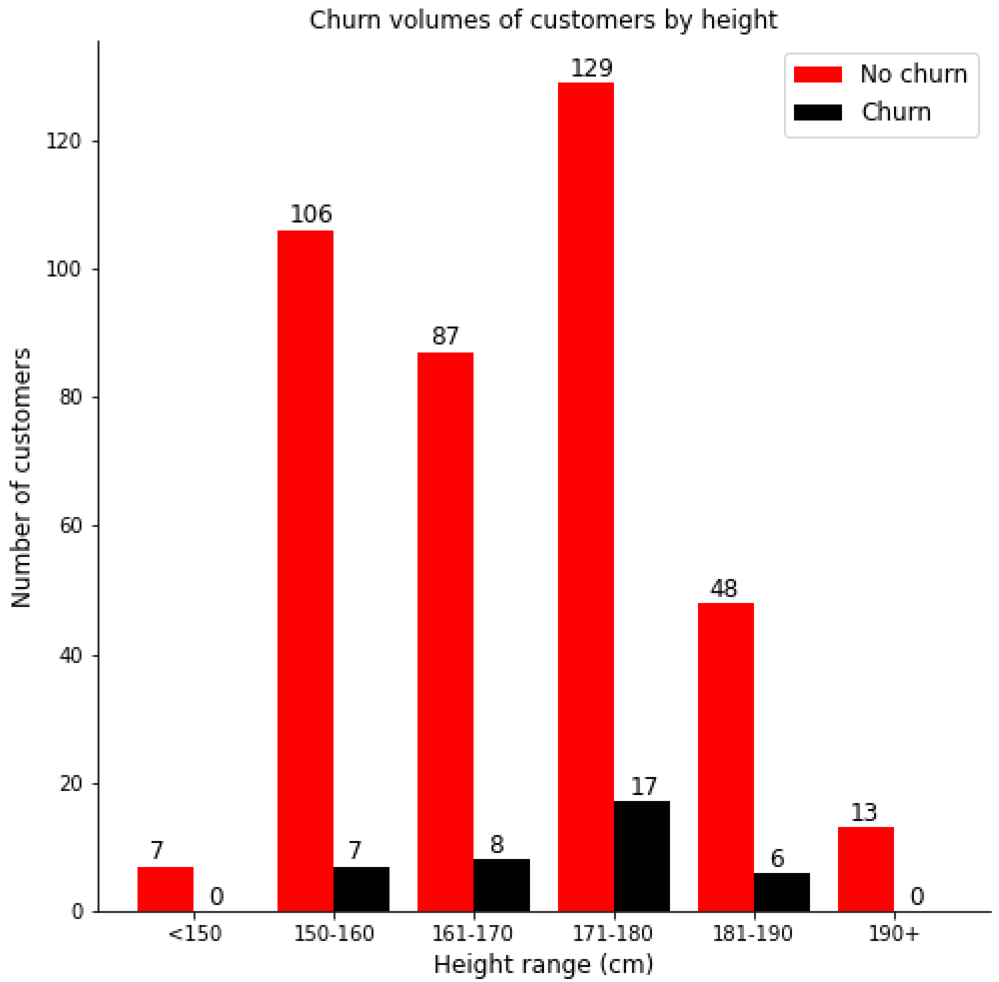


- However, men are more likely to churn – **15%** of men churned at the six week mark, **nearly double** the 8% of females who churned
- Men may feel uncomfortable as they are outnumbered in the group messaging chat function – it may be worthwhile to target **more advertising towards men**

How does age or height affect churn at Health First?

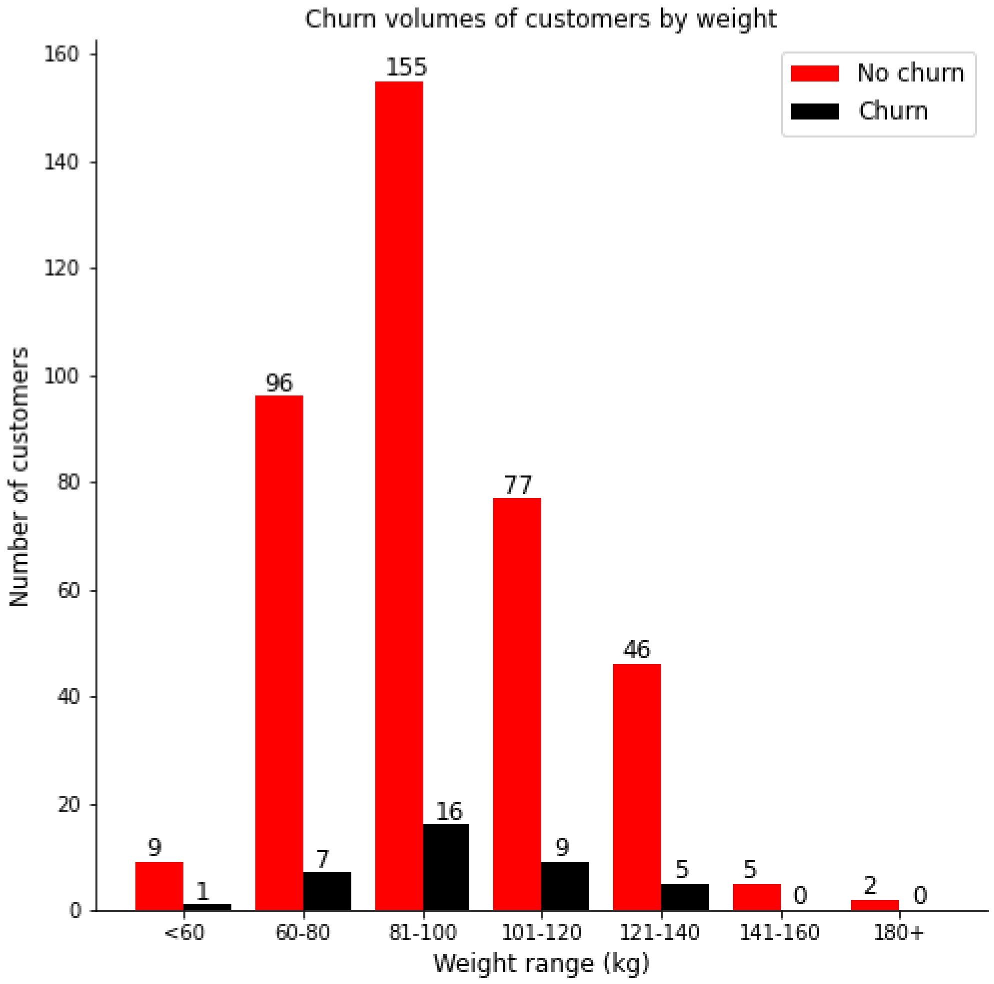
- Churn seems to be stable among all age groups – age does not seem to have a large impact on churn





- Churn is highest for customers in the 171-180cm height bracket – 12% of these customers churn, but that's very similar to the 181-190cm height bracket where 11% of customers churn

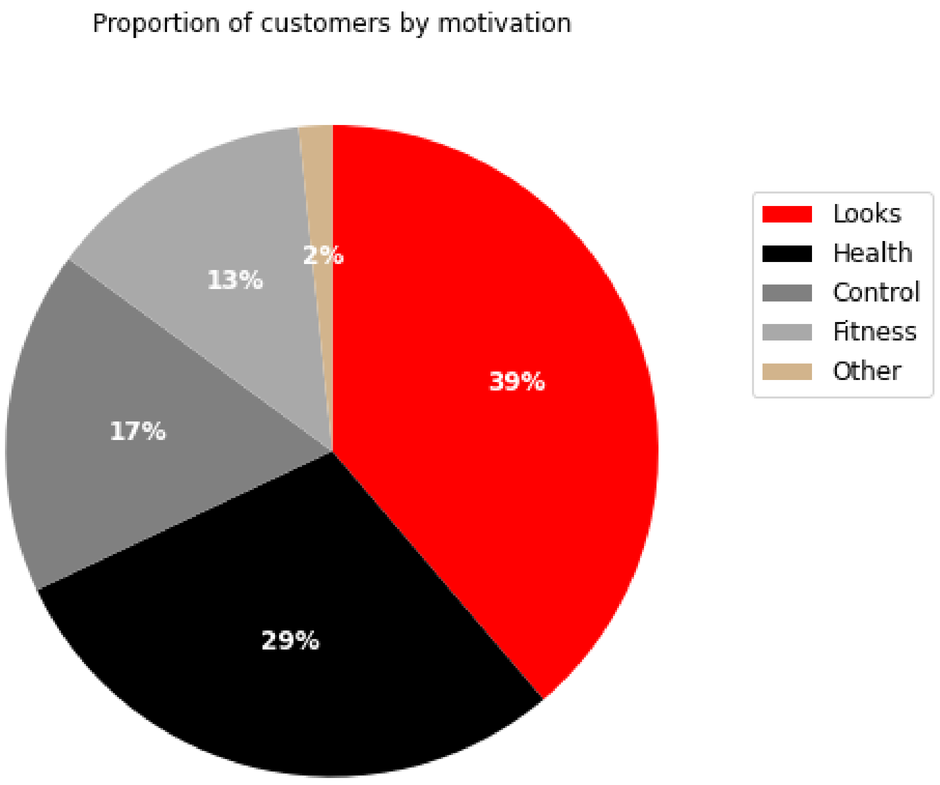
How does weight affect churn at Health First?

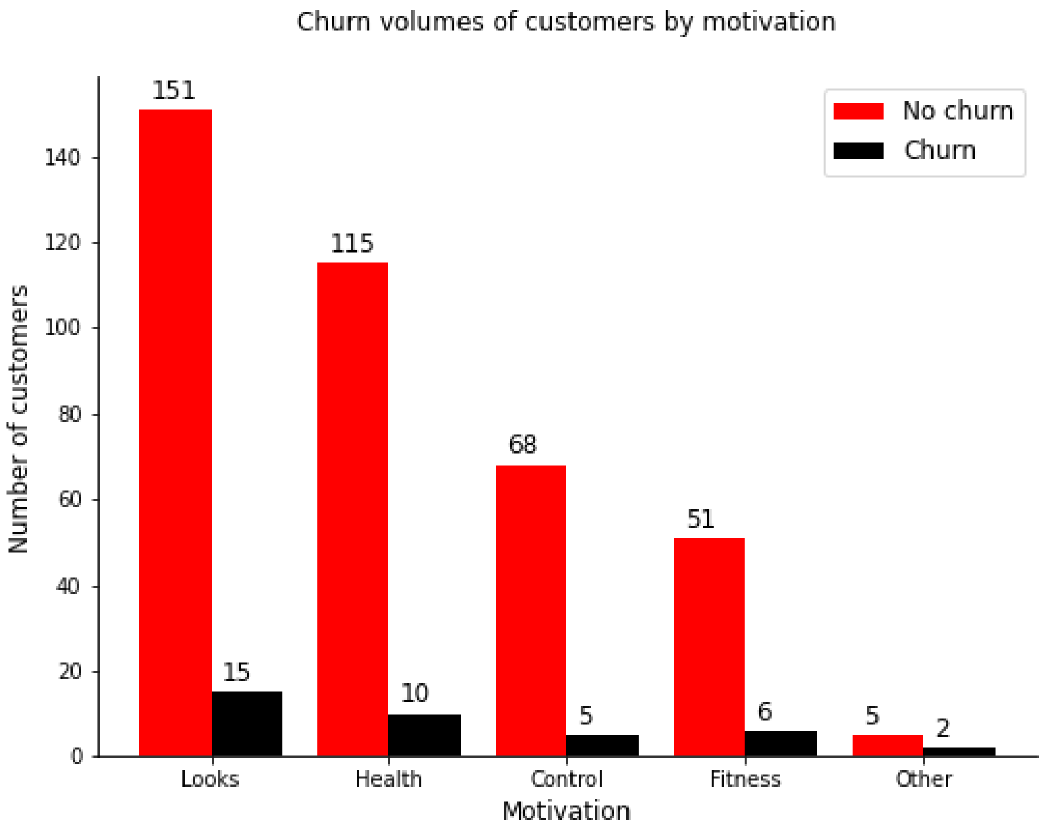


- Churn seems to be **highest in the 81-140kg** weight bracket and this weight bracket is likely when chronic illnesses begin their onset
- In order to reduce churn by these vulnerable customers, perhaps further support can be given by the mentors, e.g. **video chats** rather than just exchanging text messages
- Encouragingly, there was **no churn** among customers who weigh above 140kg. It is important that these customers stay on the program and take control of their weight loss journey

How does customer motivation affect churn at Health First?

- Customers were asked about their motivation to join Health First. The majority of customers said they wanted to improve their looks (**39%**) or improve their overall health (**29%**)

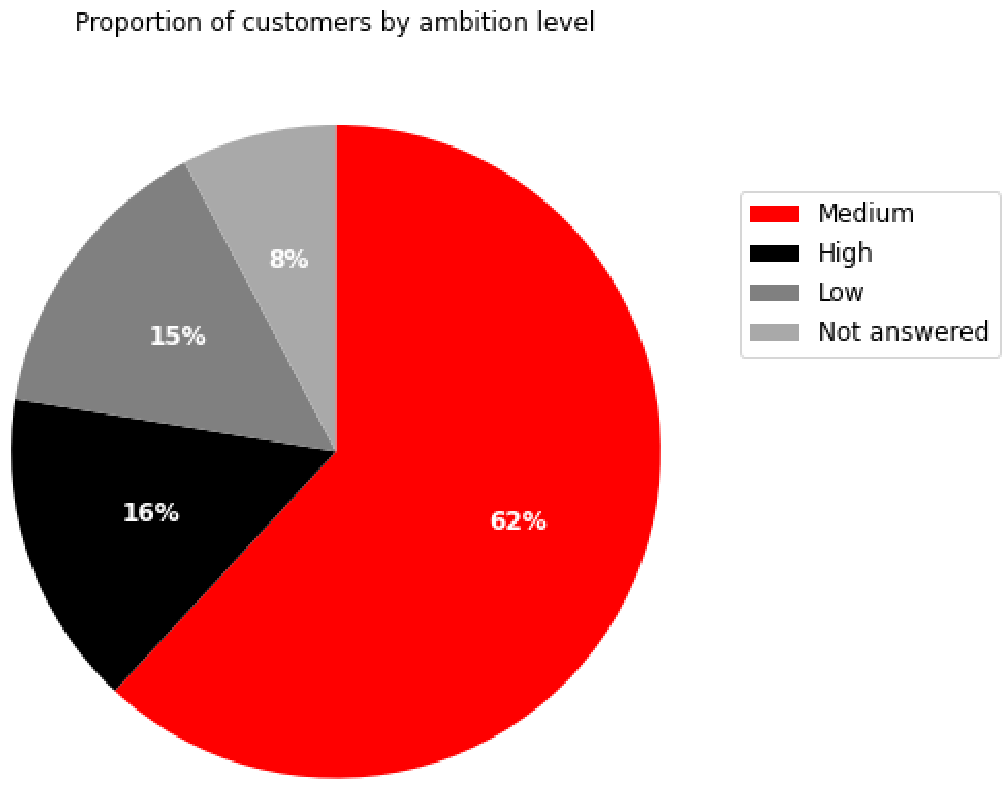


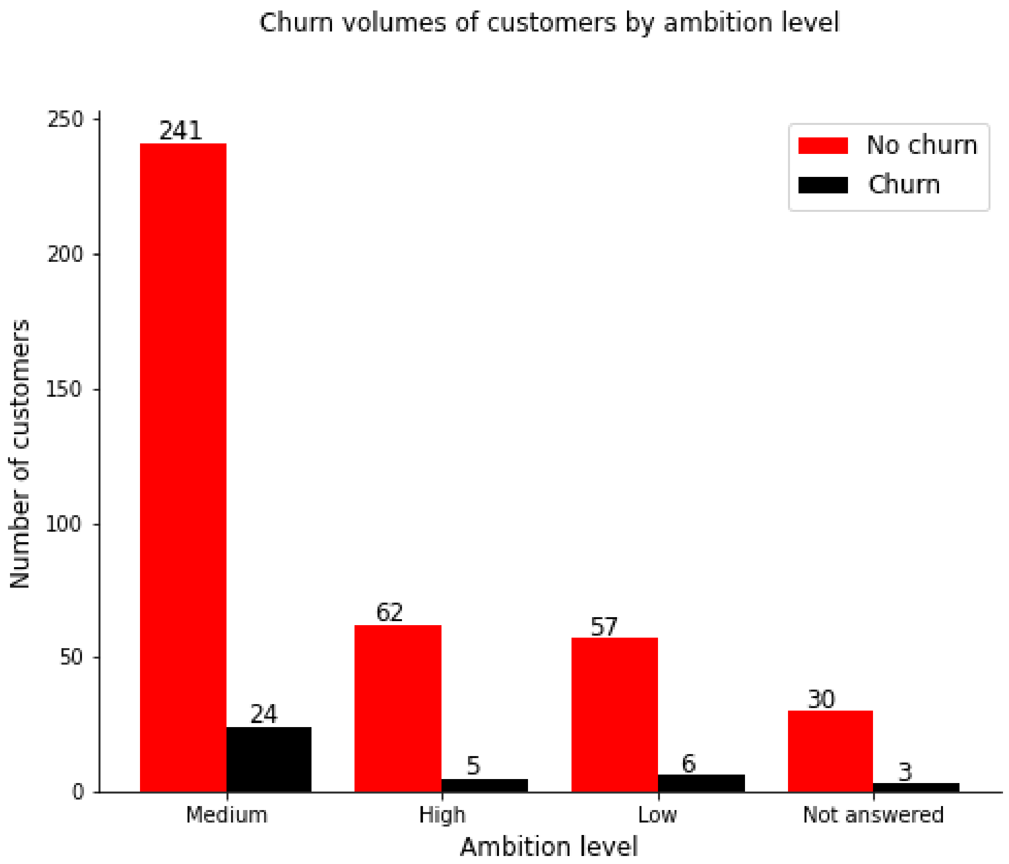


- Churn is highest among customers who joined to improve their fitness levels – **11%** of these customers churned
- **9%** of those who wanted to improve their looks churned compared to **8%** who wanted to improve their health

How do customer goals affect churn at Health First?

- Customers were asked how they like to set their goals, e.g. ambitious, conservative etc. The majority of customers chose to set moderate goals

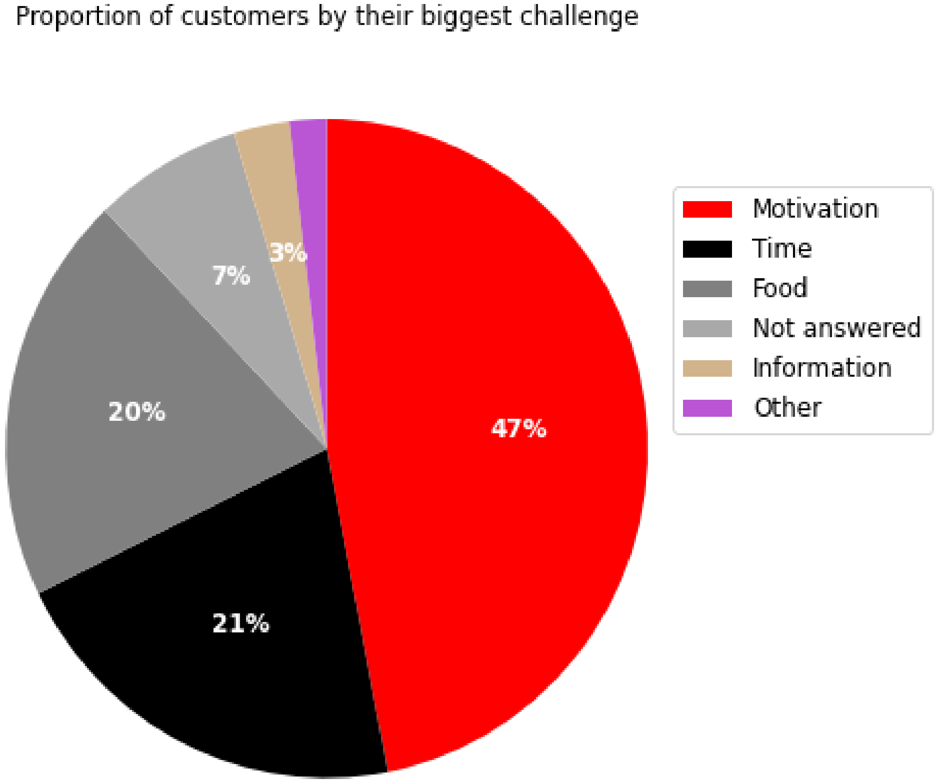


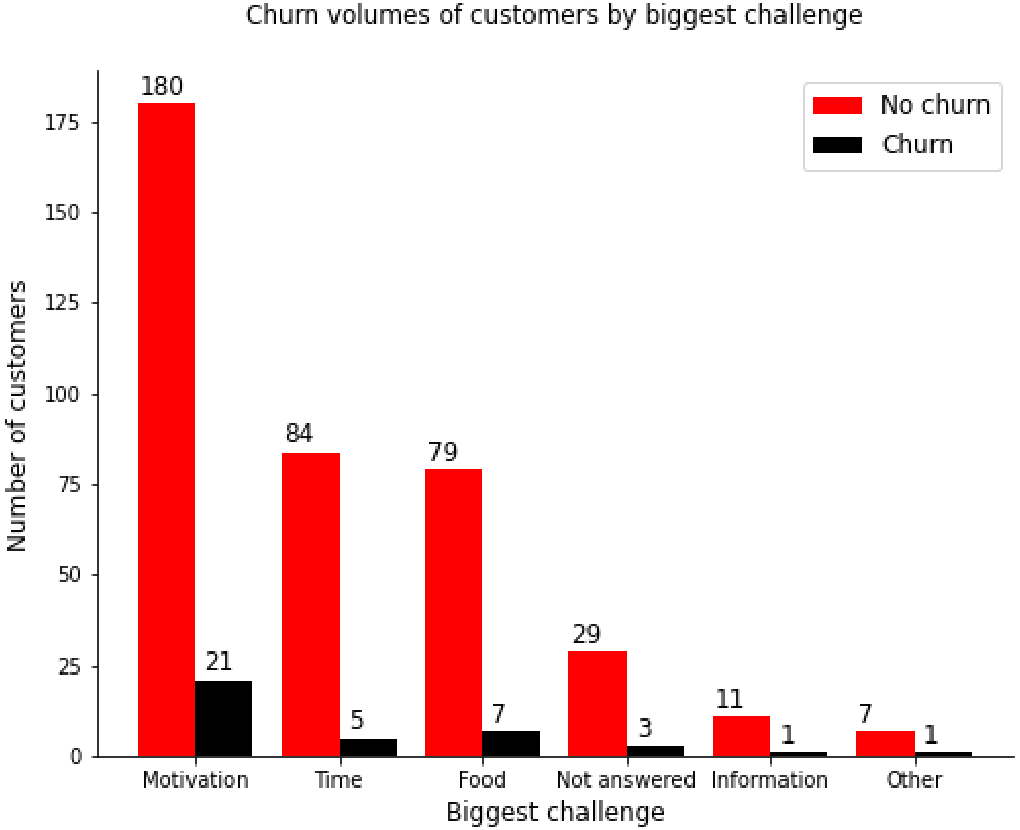


- **9%** of customers who set moderate goals churned compared to **7%** of those who set more ambitious goals, although absolute numbers may be too small to suggest this is a trend

How do customer challenges affect churn at Health First?

- **Nearly half** of customers (**47%**) said their biggest challenge was motivation and this is also the group that has the **highest churn rate**

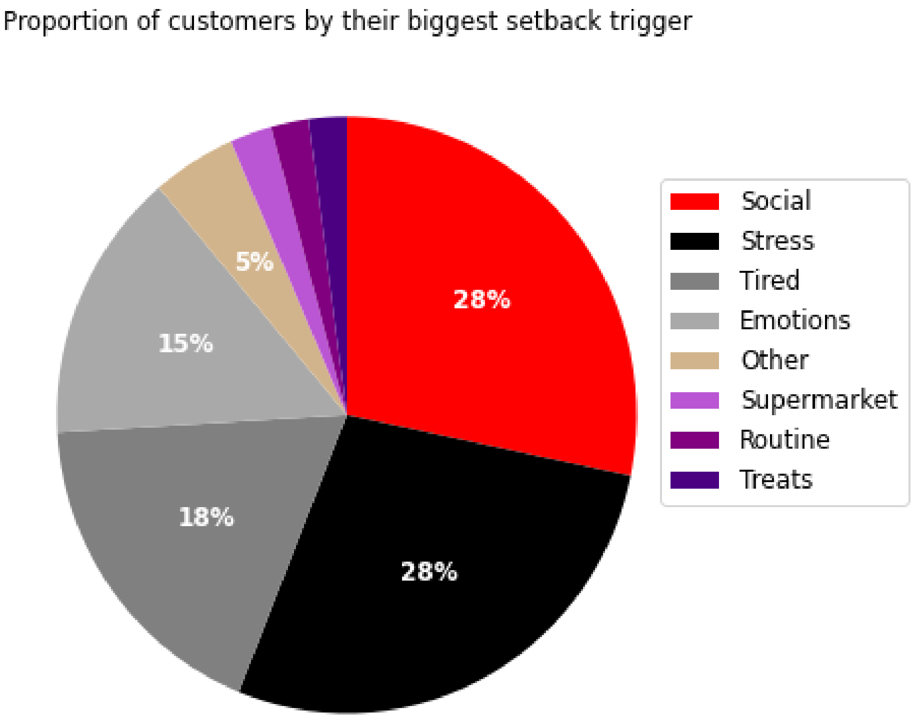


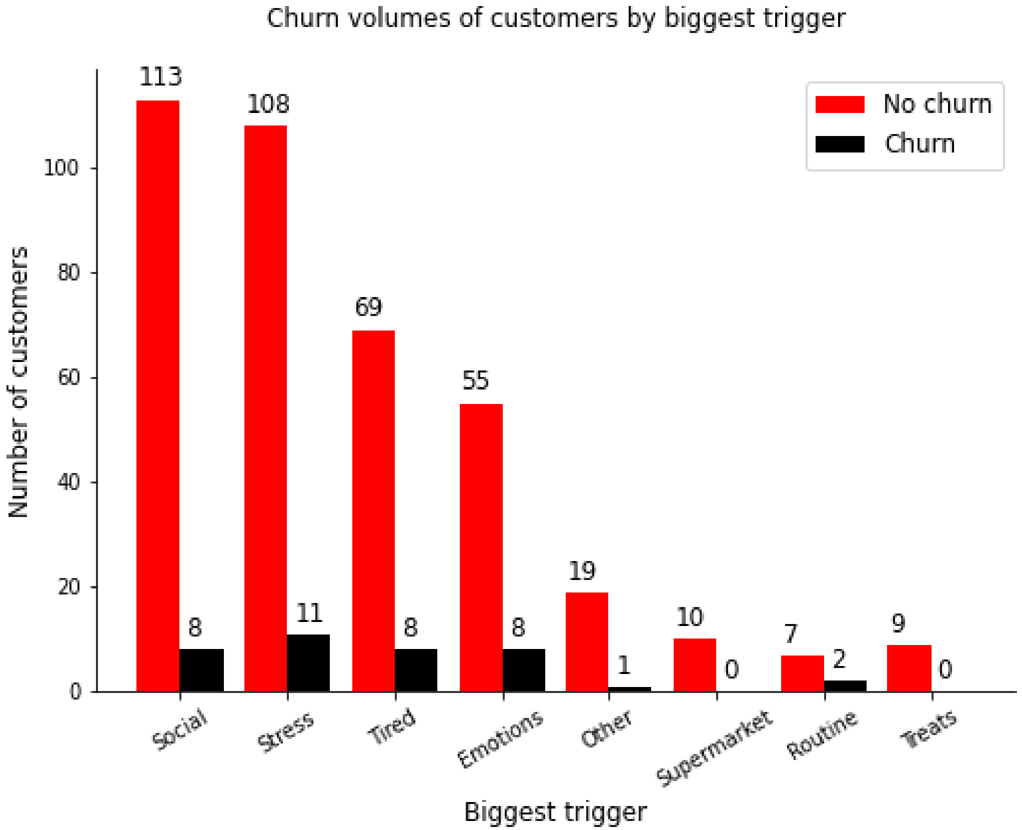


- Of those who found it difficult to motivate themselves, **10%** churned at the six week mark
- These customers may benefit from **tips on how to stay motivated**
- Alternatively, the messages platform could include a **channel dedicated to successes** where customers can share their recent success, e.g. 'lost 2kg', '5k run completed'

How do customer triggers affect churn at Health First?

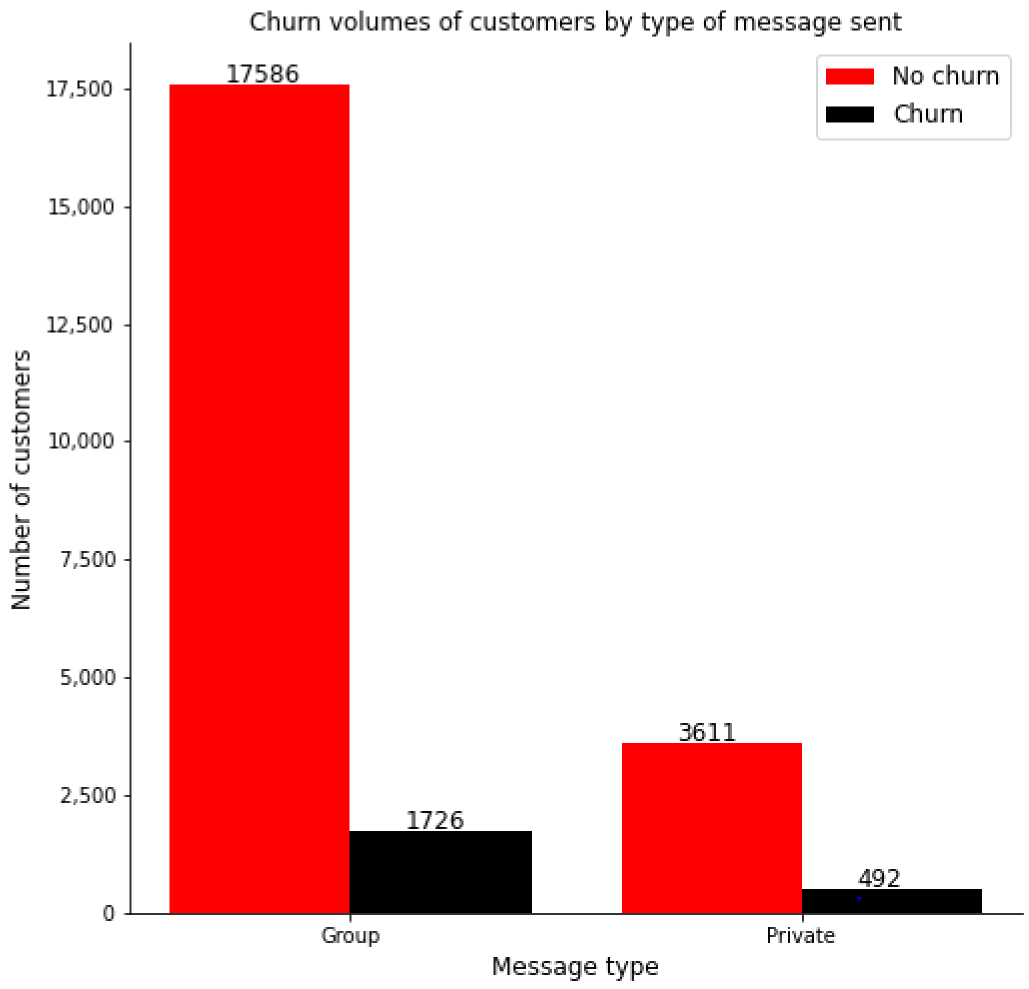
- Customers were asked which triggers stop them from moving toward their goals – most customers said their **social life**, **stress**, **tiredness** and their **emotions** were the biggest triggers





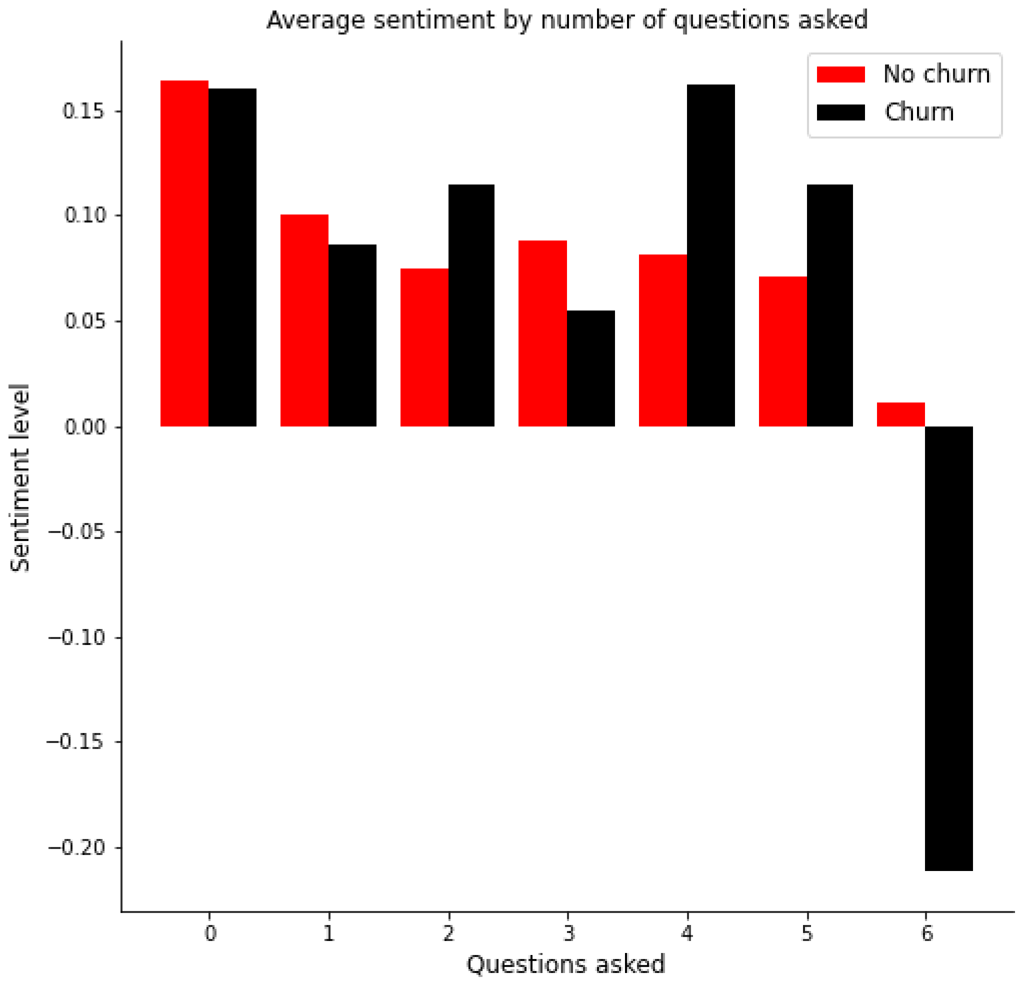
- Those who cited stress, tiredness and emotions as their biggest trigger made up **71%** of all customers who churned
- These triggers are related to **mental health** and these issues should be addressed, e.g. by including help with **meditation** and **positive thinking** or **optional therapy sessions** as part of the program

Does the type of message sent have an effect on churn?



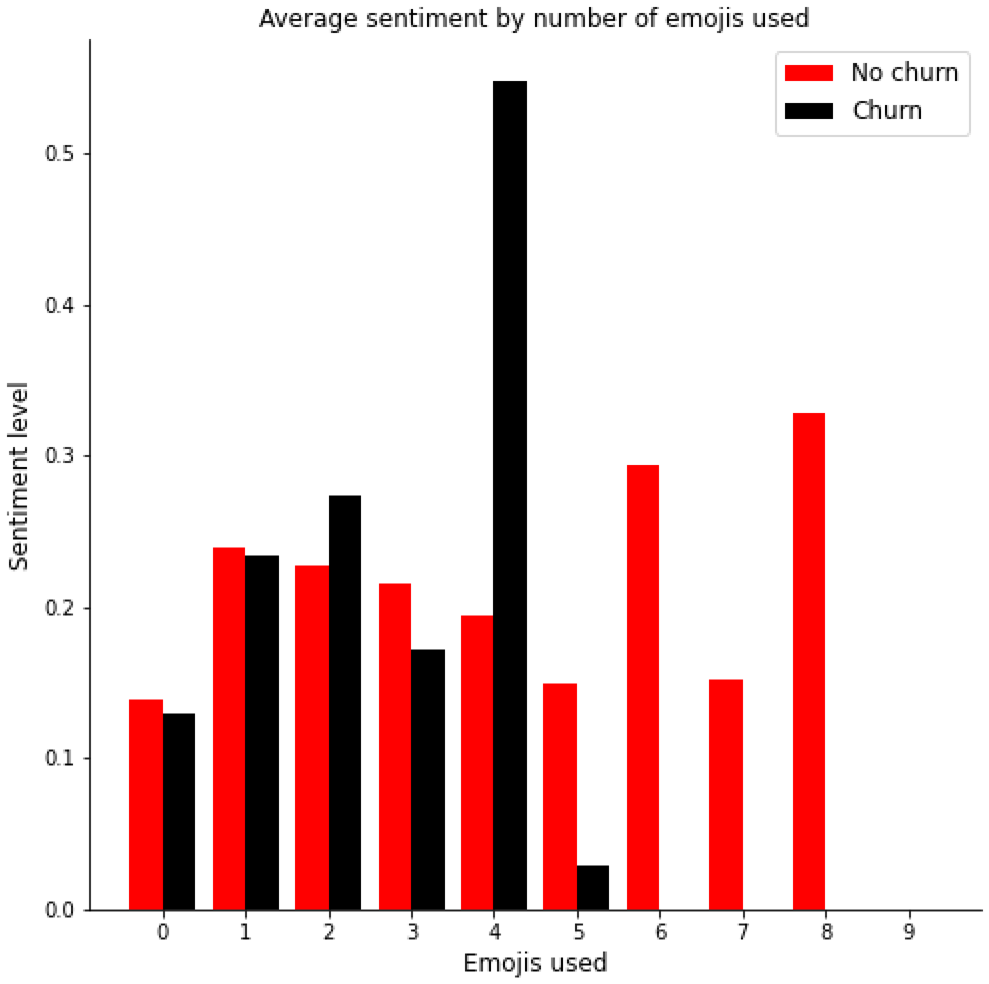
- Customers have the option of sending messages in a group chat which includes their mentor or sending private messages directly to their mentor
- Churn rates are highest for private messages – of the 4,103 private messages that were sent in the six week period, 492 (**12%**) came from customers who churned
- A potential reason for this could be because the mentor is busy and so responses to customers may be delayed. A solution could be to provide **two mentors per group**

Is there a relationship between sentiment, questions and churn?



- Sentiment is highest before any questions are asked – this is true for both those who churn and those who do not churn
- **Sentiment is higher** among those who **churned** when they asked **4 or 5 questions** – perhaps these customers learned enough information to go solo and this is the reason for churning
- The **last data point should be ignored** – this negative sentiment is attributable to one customer and does not reflect the sentiment of the group

Is there a relationship between sentiment, emojis and churn?



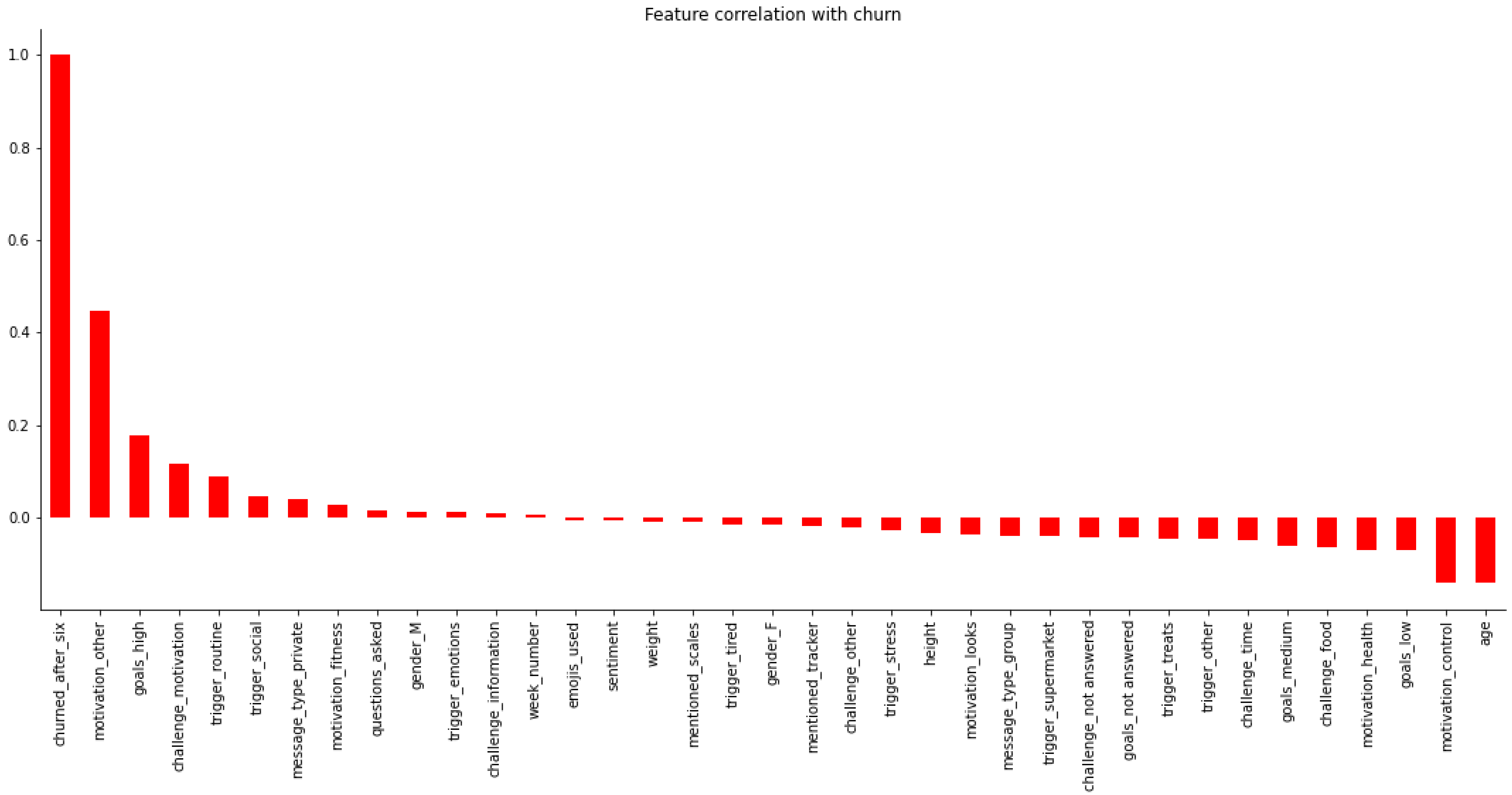
- Customers are able to send emojis as part of their messages – there is no way of knowing whether these emojis are of a positive or negative nature

- Sentiment was very high for customers who sent 4 emojis despite the fact that they churned – these may well be the same customers who asked 4 or 5 questions in the previous slide

- There was **no churn** for customers who sent **6 emojis or more** and these customers also have a **high sentiment** level – this suggests the emojis must be of a positive nature! ☺️

How do all features of the dataset correlate with churn?

- A lack of motivation and overly ambitious goals are most positively correlated with churn whereas age, lower ambitions and a desire to improve health are least correlated



Evaluating logistic regression model: confusion matrix

- The aim of the logistic regression analysis is to **reduce the number of false negatives**, i.e. those customers **we predict will not churn but they do churn**
- The logistic regression model classified 294 instances as false negatives out of the 4,683 included in the test dataset

		Prediction	
		No churn (0)	Churn (1)
Actual	No churn	True negative (TN)	False positive (FP)
	Churn	**False negative (FN)**	True positive (TP)

		Prediction	
		No churn (0)	Churn (1)
Actual	No churn	4,202	29
	Churn	**294**	158

Evaluating logistic regression model: key metrics

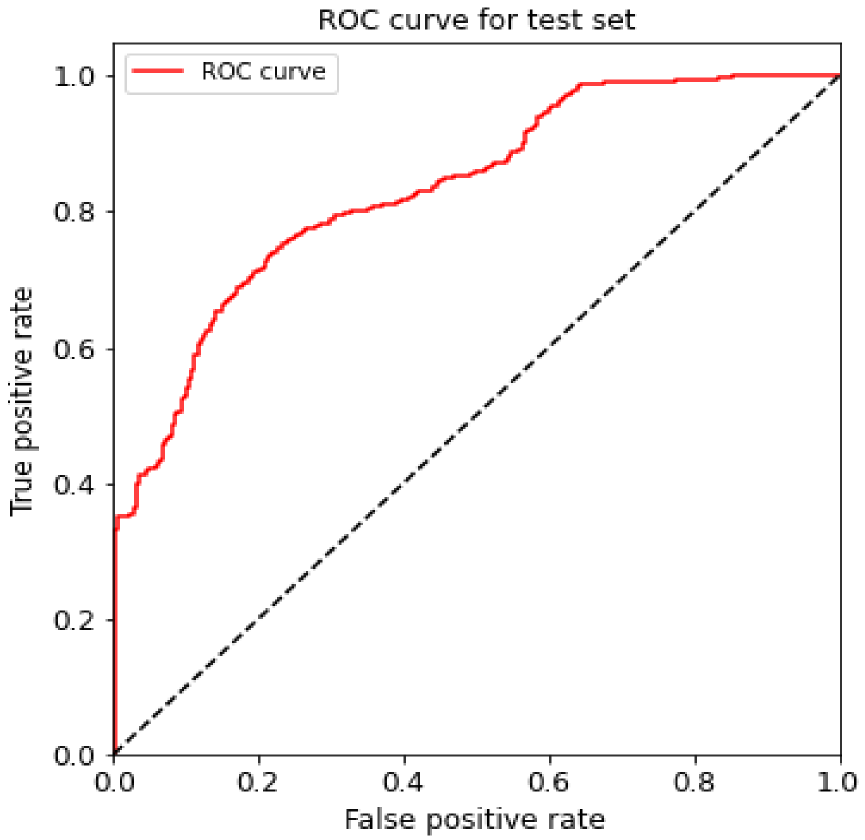
- In a churn analysis, we want to **reduce the instances of false negatives**. Therefore, we are trying to optimise the **recall** metric which shows what percentage of the class we are interested in was captured by the model

- In other words, **out of the customers that churned, what percentage did the model predict as 'going to churn'?**

- The recall score for the logistic regression model is **35%**

	Precision	Recall	Accuracy	F1 score
Calculation	TP / (TP + FP)	TP / (TP + FN)	(TP + TN) / (TP + FP + TN + FN)	2 * (Precision * Recall) / (Precision + Recall)
Result	0.84	**0.35**	0.93	0.49

Evaluating logistic regression model: ROC curve and AUC



- The ROC (receiver operator characteristic) curve is another way to **evaluate the model** visually
- The true positive rate is mapped against the false positive rate of the classifier.
- The best models will have an **ROC curve that hugs the upper left corner of the graph** – i.e. the model correctly classifies the positives more often than it incorrectly classify them.
- The curve here is in the **upper portion of the grid and also quite far off the 50% line** which is encouraging and suggests the model is fairly robust
- The AUC (area under curve) score is **0.83** which is also a pretty good score (AUC score can be between 0 and 1)

Predicting churn for ten new customers

- The logistic regression model was used to predict whether or not the ten customers who did not yet have a value for churn did indeed churn or not
- The model predicted that **all ten** of these customers **would not churn**
- This could be a true prediction given that 91% of customers did not churn during the six week period
- But the prediction result could also be due to the **dataset being imbalanced**, i.e. there are far more customers who did not churn so the model has very **few customers** who did churn to **learn from** and therefore base predictions on

Conclusion

- In terms of customer demographics, male customers are more likely to churn - this could be addressed by targeting more **advertising toward men** to encourage more male members to join
- Encouragingly, those in the highest weight categories are least likely to churn, but there are some customers in vulnerable weight categories who do churn – they could be offered additional support to reduce churn, e.g. **video chats**
- A lack of motivation is the biggest challenge for customers – adding a **'success' channel to the chat function** could help motivate these customers and reduce churn
- Stress, tiredness and emotions were the triggers listed by **71%** of customers who churned – a **mental health** product which includes **meditation guidance** and information about the **power of positive thinking** within the app, or **onsite therapists** could reduce churn
- In terms of messages sent, churn rates were highest amongst private messages – if this is due to mentors being overworked, trialling **two mentors per group** could be a solution
- The logistic regression model had an accuracy score of 93% and this high score is not surprising given that the dataset was **quite imbalanced** with only 9% of customers churning. The recall score was low at 35%
- The analysis could be improved by **excluding features** with little correlation with churn as these could be creating noise, **tuning the model** or training the data on a **different model**, e.g. Random Forest

Thank you

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