Clipboard Health Growth Strategy Case

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What was CAC in October?

CAC in October 2022 was $753.78.

Measuring CAC

1. What is the equation for finding CAC?

Customer acquisition cost (CAC) consists of all marketing costs divided by the number of customers acquired during a measured period. In Clipboard's case, marketing costs include a referral bonus, slightly altering the CAC formula:

$$CAC = \frac{(Cost_{marketing} + Cost_{referral})}{Customers}$$

Determining referral cost requires the number of referral customers acquired.

2. What type of customers were included in October's CAC?

Acquired customers were defined for this study as HCPs whose accounts showed at least 1 shift worked in 2022. For sake of simplicity, only active accounts opened in October were considered an October acquisition, even if an HCP's first shift was completed in November or later. Cases where an HCP was exposed to an earlier campaign but opened an account through an October campaign were not possible to ascertain. Time of account creation determines attribution. The resulting CAC measured this way will change over time, but should converge to true CAC after 2 or 3 months.

Data analysis

1. What data sources were used for analysis?

The required information for evaluating CAC was found within the paid marketing data and the HCP data. Paid marketing data displays campaigns and costs from the 4th quarter of 2022. The HCP data covers all user accounts created in 2022 including those that were never activated.

```
campaigns.head()
```

	CAMPAIGN_ID	CAMPAIGN_TYPE	DAY	COST	IMPRESSIONS	CLICKS
0	13743509691	Google Search	9/1/22	$199.36	1,184	57
1	13743509691	Google Search	9/3/22	$108.69	105	31
2	13743509691	Google Search	9/4/22	$188.79	794	49
3	13743509691	Google Search	9/5/22	$198.47	1,069	52
4	13743509691	Google Search	9/8/22	$900.51	2,979	213

Figure 1. Marketing data after loading in Pandas

2. What tools were used?

Although SQL is preferred for performing calculations, the two files were analyzed using Pandas dataframes for the ease in loading csv formats, rather than creating an SQL database. Pandas is executed through Python and works well for data analysis when coding in Jupyter Notebook, an online tool for writing and reviewing code in real-time.

Excel was initially used to explore datasets and brainstorm how to best extract relevant information. All files and code were stored in a Git repository to save progress and can be accessed at: https://github.com/beezmo/Clipboard.

3. Explain more about Pandas.

Pandas provides a framework to store data for easy loading and manipulation using Python code. Data is held in tables called dataframes. Datapoints are easily converted into types like dates or integers, allowing functions like sorting. For this exercise, the values in the campaign data's cost column were set to a float datatype, for storing fractional numbers, which enabled math operations on campaign costs like sums or averages. Before converting, Pandas requires the $ symbol and commas removed.

4. What assumptions were made?

The main assumption was attributing HCPs to the date when they created an account, for reasons previously mentioned. Another assumption was defining accounts without a shift as forever inactive. While there is a good chance more October acquisitions complete a first shift after the dataset, working with limited data requires some degree of freedom in the final value.

5. What was October's marketing cost? How was it measured?

The total amount spent on October campaigns was **$815,061.30**.

Calculating this figure required reducing the paid marketing data to a dataframe of only October campaigns. To get from the original dataset in fig. 1 to the desired set in fig. 2: check for inconsistencies like null values, remove $ symbol and commas in cost column, change datatypes of day and cost columns, and filter out any non-October dates.

```python
# Filter only October dates to new df
campaigns = campaigns.set_index('DAY')
oct_campaigns = campaigns.loc['2022-10']
```

```python
oct_campaigns.head()
```

DAY	CAMPAIGN_ID	COST
2022-10-01	13743509691	309.91
2022-10-02	13743509691	320.63
2022-10-03	13743509691	446.41
2022-10-06	13743509691	335.31
2022-10-08	13743509691	277.07

Figure 2. Code to reduce data to October dates and the resulting dataframe

Calculating the total amount spent in October campaigns was a simple sum function (fig. 3) of all the costs, returning a total of $815,061.30:

```python
# Calculate total spent in October
oct_campaign_total = oct_campaigns['COST'].sum()
oct_campaign_total
```

```
815061.3
```

Figure 3. Total spent in October campaigns

6. What was October's number of acquisitions? How was it measured?

The number of acquired customers for October was **1,340**.

This information was obatined from the HCP dataset. The first step was reducing the original dataframe (fig. 4) to only show accounts that worked a shift, via dropping rows with a null value in FIRST_SHIFT_TIME. Only accounts created in October are desired, therefore all other months were filtered out in the CREATED_AT column.

	HCP_ID	MSA	QUALIFICATION	CREATED_AT	LICENSE_REVIEWED	ONBOARD_AT	FIRST_CLAIM_TIME	FIRST_SHIFT_TIME
0	633be91bfb9a096b9e4d3a82	Wichita, KS	CNA	10/5/22	10/13/22	10/29/22	11/1/22	11/21/22
1	632d018f9603d7808339a6bb	Tampa-St. Petersburg-Clearwater, FL	CNA	9/23/22	NaN	NaN	NaN	NaN
2	6361931a7ccb0c3b06407c33	Scranton--Wilkes-Barre, PA	RN	11/1/22	11/1/22	NaN	NaN	NaN
3	62feb63c88ad3001baf3108f	St. Louis, MO-IL	CNA	8/18/22	8/18/22	NaN	NaN	NaN
4	63841ac43540dfe4c2ec0996	Cincinnati, OH-KY-IN	CNA	11/28/22	11/28/22	NaN	NaN	NaN

Figure 4. Slice of raw HCP dataset in Pandas

From the example in fig. 4, only the first row is an acquired working customer, indicated by the date in FIRST_SHIFT_TIME. Because the account was created on 10/5/22, this customer was included in the October CAC calculation. If any of the inactive accounts shown ever completes a shift, they would still be ignored from October's CAC.

7. What was October's referral cost? How was it measured?

The total amount spent on October referrals was **$195,000**.

October's total referral bonus cost is a function of the number of referral accounts acquired in October. From a dataframe of only October's working acquisitions, a final filter removes rows with a null value in the referrer column, yielding October's working referral acquisitions. A total of 650 accounts created in October claimed a $300 referral, which totals $195,000.

Putting it all together

1. What is the final takeaway?

```python
# Number of October HCP acquisitions
oct_hcp_acq = oct_hcp['HCP_ID'].count()

# Working referral accounts
oct_working_ref = oct_hcp['REFERRER'].count()

# Referral costs paid
oct_referral_cost = oct_working_ref * 300

# Calculate CAC: (click ads + referral fees) / HCP acquired in October
CAC = (oct_campaign_total + oct_referral_cost) / oct_hcp_acq

print('Campaign costs in October: ' + str(oct_campaign_total))
print('Number of customers acquired in October: ' + str(oct_hcp_acq))
print('Number of referred customers acquired in October: ' + str(oct_working_ref))
print('Referral bonuses paid to October acquisitions: ' + str(oct_referral_cost))
print('CAC in October: ' + str(round(CAC,2)))
```

```
Campaign costs in October: 815061.3
Number of customers acquired in October: 1340
Number of referred customers acquired in October: 650
Referral bonuses paid to October acquisitions: 195000
CAC in October: 753.78
```

Figure 5. Final CAC calculations

October's CAC was calculated in Python as $753.78. This was measured by adding campaign costs, $815,061.30, to the referral program costs, $195,000. Total spent was $1,010,061.30 to acquire 1,340 customers in October 2022, or $753.78 each.

Several concessions were made to simplify the model, trading absolute accuracy, such as the strict definition of an October acquisition. The main purpose of evaluating CAC is to track marketing performance over different time periods. As long as the method for calculating it is consistent across periods, efforts to seek greater accuracy may not add much benefit.

9. Can improvements be made for a more accurate CAC?

Additional data or studies would improve accuracy. An updated HCP dataset could reveal more October accounts took on a first shift. Conducting surveys at sign up asking when an HCP first heard of Clipboard or saw an advertisement can help attribute acquisition times correctly. However, a survey is likely unreliable anyway and true CAC might be something unattainable.

How much would you be willing to increase the referral bonus in Los Angeles and Nashville? Why?

For both L.A. and Nashville, I would be willing to increase the referral bonus by $50, for a total of $350, or $175 each to the referrer and referee. Strictly from a financial perspective, this increase requires a small effect on HCP acquisition rates to break even on additional costs, ie. 2.6% for both cities. As bonus levels increase, greater acquisition rates are needed to offset payouts. Thus, $350 was decided as a reasonable starting point.

Measuring effects of referral bonus increases

1. What are the effects of a bonus increase?

Referral bonuses are a method of increasing customer acquisition and follow laws of supply and demand. Greater quantities of HCPs are willing to supply their labor as referral bonuses increase. Thus, an additional bonus results in increased referral numbers, from which a certain percentage may decide to take shifts regularly and perhaps even refer others themselves. Fill rates would also improve, delighting facility customers.

Surely, an increase has lasting effects beyond the initial bonus payout. However, if bonuses are set too high and acquisitions fall short of goals, profits may have been better had bonus remained untouched. Goodwill from facilities is always beneficial but the decision here focuses on the quantifiable returns from staffing services. The approach in this study was to determine the cost of a bonus increase and the effect needed on acquisitions to offset those costs.

2. Why was $350 chosen?

With current referral bonus payments at $300, a minimal increment was desired for initial analysis. Humans naturally respond to multiples of 5 and 10 and from the individual HCP's perspective, an extra $25 seemed signifcant enough to entice the next block of potential acquisitions. Advertising the 16% boost could in turn boost referral rates and conversion rates.

After creating a model of L.A. and Nashville's referral programs, profits are measured for different inputs of bonus levels and acquisition rates. For either city, inputting an increase to $350 suggests a gain in profits if the effect generates 3% in added referrals. For an incremental increase to $400, both cities need over 5% boosts in acquisitions. The gains do not include added benefits from a larger workforce and increased facility goodwill. If a $350 bonus proves successful, more studies into another boost are warranted.

3. How was the referral program modeled?

The referral program was modeled by predicting acquisition numbers over a 5 year period. Values from the dataset initialize the model, such as number of accounts. Statistics are calculated for projection formulas and assumed to stay (mostly) constant each year. These include referral conversion rate, revenue earned per referral, etc. Additional data would improve projection accuracy, but estimates are substituted for simplicity.

Once referral acquisitions are projected for each year, revenues are calculated. Subtracting bonus costs returns profit. Converting every year's profit to current dollar value and summing gives a single present day value. Inputs are adjusted to observe different scenarios, deriving present day values for each to identify which option offers greater profitability.

4. How were the effects of a bonus increase measured?

Instead of predicting the consequence of a bonus raise on acquisition numbers, the model works backwards to discover the minimum effects needed to justify a given bonus amount. The decision to okay a $50 increase is only because the model determined a reasonable target of ~3% additional referral accounts makes up for cost. The decision would be much less enticing if the same $50 increase required 15% of effect to break even.

5. How accurate is the model?

The model's purpose is not in predicting profit, rather it best serves as a comparison tool. Even if growth calculations are inaccurate, as long as the inaccuracies remain consistent between tests at $300 versus $350, then final valuations will reveal the better option. Still, additional research to replace estimates and assumptions with truer representations would improve the model.

6. What are the assumptions?

Many of the measurements for predicting growth were evaluated from a single year of data. The model assumes that they stay somewhat constant for each of the next 5 years. In other words, the acquisition growth from one year to the next mirrors 2022 rates if bonus remains constant. Some impactful values were set arbitrarily because of insufficient data like growth rates of non-referral accounts, churn, and average working life expectancy.

Minor assumptions include HCPs without shifts will never convert, HCPs cannot change their role type, all shifts worked take place in the reported MSA, and shift availability remains constant with respect to HCP demand. An HCP forgetting to submit a referral should technically be included as a referral acquisition, but this is impossible to determine and therefore ignored. As already mentioned, more research and data would improve the model but this version is still effective for evaluation purposes.

Technical details of the model

1. What is the general overview of the final model?

A discounted cash flow model (fig. 6) was created in Excel to forecast outcomes. Inputting datapoints extracted from each city's analysis projects MSA referral programs to 2027.

The left two-thirds displays forecasted calculations, consisting of the financial results, outlined in the black box, which are derived from the acquisition numbers in the green box. Below finances are statistics to check if year over year comparisons are within reasonable parameters. The gray column initializes the model using the provided 2022 HCP data. On the right side in red, adjustable inputs are used in forecasting acquisition numbers.

	FY2022	FY2023	FY2024	FY2025	FY2026	FY2027
Referral Accounts (incl nonconverted)	620.0	884.4	1,663.9	2,220.0	3,065.7	3,956.2
Expected Referrals from Bonus Increase	0.0	22.9	43.2	57.6	79.6	102.7
Total New Referral Accounts	**620.0**	**907.3**	**1,707.1**	**2,277.6**	**3,145.2**	**4,058.9**
Converted New Referral Accounts	453.0	663.3	1,247.9	1,664.9	2,299.2	2,967.1
Returning Referral Accounts	0.0	453.0	1,071.0	2,252.5	3,507.3	4,936.7
Retired Referral Accounts	0.0			285.4	703.2	1,489.4
Referral Accounts Churned	0.0	45.3	66.3	124.8	166.5	229.9
Active Referral Accounts	**453.0**	**1,071.0**	**2,252.5**	**3,507.3**	**4,936.7**	**6,184.4**
Retired Nonreferral Accounts	0.0			590.8	945.3	1,323.4
Active Nonreferral Accounts	**844.0**	**1,350.4**	**1,890.6**	**2,646.8**	**3,705.5**	**3,864.3**
TOTAL ACTIVE ACCOUNTS	**1,297.0**	**2,421.4**	**4,143.1**	**6,154.0**	**8,642.2**	**10,048.7**
Revenue per Referred Account	$784	$745	$708	$672	$652	$632
Revenue per Legacy Referred Account	$1,066	$1,012	$962	$914	$886	$860
Total Referral Revenue	**$355,161**	**$952,591**	**$1,912,930**	**$2,916,392**	**$3,984,129**	**$4,840,005**
Referral Bonus	$300	$350	$350	$350	$350	$350
Total Bonus Cost	**$135,900**	**$232,138**	**$436,758**	**$582,725**	**$804,708**	**$1,038,468**
Total Referral Program Profit	**$219,261**	**$720,454**	**$1,476,172**	**$2,333,667**	**$3,179,422**	**$3,801,537**
Posted Shifts	189,628.0	265,479.2	371,670.9	446,005.1	535,206.1	561,966.4
Available Shifts per Account	146.2	109.6	89.7	72.5	61.9	55.9
Y/Y						
New Referral Accounts		**46.34%**	**88.15%**	**33.42%**	**38.09%**	**29.05%**
Active Referral Accounts		**136.41%**	**110.33%**	**55.70%**	**40.76%**	**25.27%**
Nonreferral Accounts		**60.00%**	**40.00%**	**40.00%**	**40.00%**	**4.29%**
Total Active Accounts		**86.69%**	**71.11%**	**48.54%**	**40.43%**	**16.28%**
Posted Shifts		**40.00%**	**40.00%**	**20.00%**	**20.00%**	**5.00%**

Referral Factors	
Referral Bonus	350
Effect of Bonus Increase	2.6%
Account Growth	20.0%
Referral Conversion Rate	73.1%
Posted Shifts Growth	20.0%
Churn %	10.0%
% of Accounts Referring Others	28.1%
Referrals per Referrer	1.70
General	
Interest Rate	4.0%
Degree of Freedom	2.0%
NPV with Changes	$9,531,242.52
NPV without Changes	$9,531,134.34

Figure 6. Cash flow forecast for L.A.'s referral program over 5 years

Net present values (NPV) are calculated with an Excel formula in the blue box. It discounts the 5 years of cash flows by a yearly interest rate into a single value at today's dollars. NPV allows for testing different scenarios in terms of present value added. The bottom NPV is the projected profit for keeping referrals at $300. After setting the bonus to $350 (1st value in the red box), the acquisition effect (2nd value, red box) is adjusted until the top NPV surpasses the bottom. When the two values converge, the break even point is found. 2.6% is the minimum target for a bonus of $350. The second line in the green box shows the bump in referrals.

2. How were profits calculated?

For any given year, referral program profits equals revenue earned from all referral accounts minus bonuses paid to *new* referrals. The model assumes legacy referral accounts from the previous year will continue on and earn more than newly acquired HCPs by taking shifts for the full year. Thus, the profit for a given year follows the formula:

$$Year\ Profit = (R_L * x) + (R_N * y) - (C * y)$$

R_L: *revenue per legacy referral*
R_N: *revenue per new referral*
x: *number of legacy referral accounts*
y: *number of new referral accounts*
C: *Cost of referral bonus*

This logic is represented by the black outlined projections in fig. 6. Using the formula for each of the next 5 years gives a cash flow series that is valued with NPV. Deciding on values for each of the variables is where forecasting begins.

3. How was revenue per referral found?

Initializing values for $\boldsymbol{R_L}$ and $\boldsymbol{R_N}$ requires filtering datasets down to only active HCP accounts that claimed a referral. Depending on role type, every filled shift earns Clipboard either $40, $80, or $120. For example, a LVN is paid $240 for an 8 hour shift and Clipboard receives $320, leaving a profit difference of $80. Averaging the profits gives revenue per account.

Because the HCP data is limited to 2022 acquisitions, $\boldsymbol{R_L}$ was estimated by ignoring referral acquisitions from the 2nd half of 2022, ie. removing accounts too new for consideration. For $\boldsymbol{R_N}$, all of 2022 was used. In the model, $\boldsymbol{R_L}$ and $\boldsymbol{R_N}$ decrease each year by a small percentage to account for growth in accounts.

4. How were the other variables found?

The value for $\boldsymbol{C}$ is simply the referral bonus. Finding initial values for $\boldsymbol{x}$ and $\boldsymbol{y}$ was a matter of counting the number of accounts in the filtered datasets, already done from calculating $\boldsymbol{R_L}$ and $\boldsymbol{R_N}$. Only new accounts, $\boldsymbol{y}$, is multiplied by $\boldsymbol{C}$ as bonuses were already paid out to $\boldsymbol{x}$ in past years.

After initialization, future values of $\boldsymbol{x}$ and $\boldsymbol{y}$ were determined with forecasting. This step required much of the analysis efforts.

5. How were referrals forecasted?

Future values for $\boldsymbol{x}$ are found by carrying over accounts from the prior year, less any churn. Future values for $\boldsymbol{y}$ involve some extra steps and make up most of the model's calculations. New referrals are a function of the percent of current users that refer others.

First, the number of unique referrers are found from HCP data. Dividing by the number of active accounts, including nonreferrals, reveals the percent of users who refer others. Next, divide total referrals by unique referrers to find average referrals per referrer. Finally, obtain referral conversion rate: working referrrals divided by all referrals, including non-activated accounts. Projecting $\boldsymbol{y}$ is now possible.

For example, if 10 users carry over from 2022 and on average 20% refer others, there are 2 users who will refer throughout 2023. If the average acquisition per referrer is 1.5, then 3 users will ultimately download the app. Lastly, if referral conversion rate is 66%, then 2 HCPs will continue on to work a shift, representing $\boldsymbol{y}$ in the profit forrmula.

6. Are there other factors affecting referral profits besides acquisition rates?

Factors that affect referral profits but required extra research/data include growth rate of non-referred HCP, churn, average working life expectancy, and interest rates and inflation. These are accounted for in the model with rough estimates. Better information would yield greater accuracy but these factors likely do not affect profit as much as the others mentioned in previous sections.

The model does not account for increased goodwill from clients filling more shifts. If Clipboard places a value on this goodwill, then even fewer referral accounts are needed to justify a bonus increase. Given L.A. and Nashville fill 89% and 66% respectively, the 25% danger zone for facility churn is not necessarily a factor. The model's decision to increase bonuses is based on the single objective of maximizing profit, ie. balancing referral cost and lifetime return.

Data analysis

1. What data sources were used for analysis?

The required information to evaluate the referral program was found within the HCP data. The shifts data was used in initial exploration and while it provided some insight, was not incorporated in the final model.

The HCP data covers all user accounts created in 2022 including those that were never activated. The shifts data records shift records of facilities in different MSAs by role type and month from 9/22 to 11/22. An outside data source on cost of living (AdvisorSmith.com) was combined with the shifts data to explore possible relationships with MSA fill rates but results were mixed and focus pivoted toward modeling with HCP data.

2. What tools were used?

SQL is preferred for calculations but the files were analyzed using Pandas dataframes for easier initial loading. Jupyter Notebook was used for writing code and performing calculations.

Some Tableau was used for visualization during an unsuccessful attempt at predicting impact on fill rates from cost of living. The resulting graph does present interesting questions for other research avenues and can be found in Appendix B. All relevant files and code were stored in a Git repository to save progress and can be accessed at: https://github.com/beezmo/Clipboard.

3. What was the first step in analysis?

When first exploring the question of how much to increase bonus, the shifts data was input into Pandas to understand why these two particular cities. After enusuring homogeneity for city names, a pivot table was created (fig. 7) to aggregate filled and posted shifts for each MSA. A new column calculates every MSA's fill rate.

```python
# Find fill rate for each MSA
fill_rate = MSA_shifts['FILLED_SHIFTS'] / MSA_shifts['POSTED_SHIFTS']
MSA_shifts['FILL_RATE'] = fill_rate
MSA_shifts
```

MSA	FILLED_SHIFTS	POSTED_SHIFTS	FILL_RATE
Atlanta-Sandy Springs-Alpharetta, GA	4469.0	6266.0	0.713214
Boston-Cambridge-Newton, MA-NH	1860.0	3085.0	0.602917
Canton-Massillon, OH	812.0	1114.0	0.728905
Chico, CA	1356.0	2591.0	0.523350
Cincinnati, OH-KY-IN	1834.0	2813.0	0.651973
Columbus, OH	1601.0	1949.0	0.821447

Figure 7. Code calculating fill rate and a sample of the resulting pivot table

4. What information was found from the shifts data?

In city comparisons of filled shifts, Nashville falls on the lower end, 66%, while L.A. contends for best rate at 89%. For reference, 79% of all shifts in the country were filled. Each MSA fills 71% on average. The two cities also fall on opposite ends of the spectrum in terms of shifts posted. The average MSA posts 4,921 shifts, whereas Nashville posted under half that and L.A. listed nearly 10x, despite a strong fill rate.

At first glance, the data suggests Nashville could benefit from increasing referrals to improve fill rates and L.A. might be better off scaling back. However, fill rates are already at healthy levels for avoiding facility churn. At this realization, the approach to raising bonuses pivoted from effects on fill rates toward effects on profit. The information for measuring profits is contained in the HCP data.

5. How was HCP data analyzed?

After cleaning the HCP data in Pandas, a series of manipulations and filters reduces the original set into smaller dataframes containing only the desired type of HCPs for analysis. Over 15 dataframes were created at this step and for each, statistics were calculated to find values that factor into the model: conversion rates, referrer rates, average shifts worked, etc.

6. What were the different dataframes?

There are too many to list here and not all were even used in the final model. Most are minor variations of each other but the significant dataframes include: the original set itself, active accounts, referral accounts, active referral accounts, non-referral accounts, accounts created before July, referrals and non before July, and so on. Then reducing to the L.A. and Nashville dataframes, the same process of partitioning into referrals and actives, etc. is repeated.

```python
# Find active accounts made without a referral
la_nonref_active = la_hcp.loc[la_hcp['REFERRER']=='None'].copy()
la_nonref_active.dropna(subset = ['FIRST_SHIFT_TIME'], inplace=True)
la_nonref_active = la_nonref_active.reset_index(drop=True)
la_nonref_active.head()
```

	HCP_ID	MSA	QUALIFICATION	CREATED_AT	LICENSE_REVIEWED	ONE
0	62a255d0c50003846a02e647	Los Angeles-Long Beach-Anaheim	CNA	6/9/22	6/9/22	
1	621f2a1678c27801ac191b9b	Los Angeles-Long Beach-Anaheim	CNA	3/2/22	3/2/22	
2	633086869603d78083e0e5e1	Los Angeles-Long Beach-Anaheim	CNA	9/25/22	11/18/22	
3	62e9c57200e29d01ab56e9a2	Los Angeles-Long Beach-Anaheim	LVN	8/3/22	8/3/22	
4	626ad36d7e73ce01c14cb6e8	Los Angeles-Long Beach-	CNA	4/28/22	4/28/22	

Figure 8. Snippet of the code to produce one of the dataframes, here LA HCP active accounts without a referral

7. What were some of the datapoints gathered and show an example of the process.

Some of the more easily computed but crucial values were for initializing. For each city, the total number of accounts, referrals, active referrals, etc. These were usually a matter of filtering to the desired level of exclusivity and counting up the rows.

Many extracted statistics required multiple steps and dataframes. To find the probability that an active HCP refers others, reduce the referrer column to only unique IDs, therby counting the individual users who referred others in 2022. For L.A. this was 364 and Nashville, 48. Dividing referrers by total active HCPs reveals the chance of an active user referring others. From there find the average referrals sent by dividing total referrals by total *referrers*. For Nashville, 41% of HCPs referred others and each one recruited 1.73 others.

One of the more complicated calculations was finding revenue earned per working referral. The code in fig. 9 shows a sample for Nashville. Using a dataframe filtering only active referral accounts, the role type listed determines revenue earned per shift. For HCPs registered as CNA, Clipboard earns $5 per hour, or $40 for an 8 hour shift. Multiplying shift revenue by lifetime shifts returns total profit for that account. Averaging the profits, which is the basic logic of the fig. 9 algorithm, outputs a profit per user of $690.63. Within the year the program is already returning profits at over double the $300 referral cost, not even considering goodwill benefits. In L.A., the return was $784.02 per referral claim.

```
nash_raa_profit = 0
nash_raa_hcp = nash_ref_active['HCP_ID'].count()

cna_rate = 5
lvn_rate = 10
rn_rate = 15

for x in np.arange(nash_raa_hcp):
    if nash_ref_active.iloc[x,2] == 'CNA':
        nash_raa_profit += nash_ref_active.iloc[x,8] * cna_rate * 8
    elif nash_ref_active.iloc[x,2] == 'LVN':
        nash_raa_profit += nash_ref_active.iloc[x,8] * lvn_rate * 8
    elif nash_ref_active.iloc[x,2] == 'RN':
        nash_raa_profit += nash_ref_active.iloc[x,8] * rn_rate * 8

nash_avg_ref_profit = nash_raa_profit / nash_raa_hcp
nash_avg_ref_shifts = nash_ref_active['LIFETIME_SHIFTS'].mean()

print('Average profits from referred accounts in Nashville: ' + str(n
print('Average shifts for referred accounts in Nashville: ' + str(nas
```

```
Average profits from referred accounts in Nashville: 690.625
Average shifts for referred accounts in Nashville: 13.640625
```

Figure 9. Code to calculate return in Nashville

Walking through a working model

1. How was initialization data incorporated?

This example will focus on L.A., starting with forecasting referral acquisitions in a scenario where bonus stays the same.

	FY2022	FY2023	FY2024	FY2025	FY2026	FY2027
Referral Accounts (incl nonconverted)	620.0	884.4	1,653.2	2,184.3	2,994.1	3,839.4
Expected Referrals from Bonus Increase	0.0	0.0	0.0	0.0	0.0	0.0
Total New Referral Accounts	**620.0**	**884.4**	**1,653.2**	**2,184.3**	**2,994.1**	**3,839.4**
Converted New Referral Accounts	453.0	646.5	1,208.5	1,596.7	2,188.7	2,806.6
Returning Referral Accounts	0.0	453.0	1,054.2	2,198.0	3,388.5	4,724.9
Retired Referral Accounts	0.0			285.4	692.7	1,454.0
Referral Accounts Churned	0.0	45.3	64.6	120.9	159.7	218.9
Active Referral Accounts	**453.0**	**1,054.2**	**2,198.0**	**3,388.5**	**4,724.9**	**5,858.5**
Retired Nonreferral Accounts	0.0			590.8	945.3	1,323.4
Active Nonreferral Accounts	**844.0**	**1,350.4**	**1,890.6**	**2,646.8**	**3,705.5**	**3,864.3**
TOTAL ACTIVE ACCOUNTS	**1,297.0**	**2,404.6**	**4,088.6**	**6,035.3**	**8,430.4**	**9,722.8**

Figure 10. A possible outcome of L.A.'s referrals if bonus remains $300

The model begins by inputting values discovered from L.A.'s HCP data into the gray column where appropriate, see fig. 10. There were 620 accounts created with a referral in 2022. Not all of them actually worked. Only 453 converted to active, claiming a bonus in 2022. The last initialization input, active non-referral accounts, was 844 for L.A. Non-referral accounts do not factor into referral profits directly but contribute by referring others. In total there were 1,297 active accounts, both referral and non, in L.A in 2022.

2. How was 2023 projected?

Account churn is recorded the year after working, so the 45 churned in 2023 are from the 1,297 acquisitions in 2022. The remaining 1,252 are assumed to continue working in 2023, sometimes referring others. The model predicts 28% of those 1,252 will refer 1.7 others, like in 2022, equating to a batch of 598 acquisitions in 2023. However, these acquisitions will themselves simultaneously recruit another generation of referrals. Assuming again 28% of 598 HCPs refer 1.7 others, a total of 884.4 referral accounts are now projected for 2023. The bottom two values in fig. 11 store the relevant statistics used in forecasting referral numbers.

Referral Factors	
Referral Bonus	300
Effect of Bonus Increase	0.0%
Account Growth	20.0%
Referral Conversion Rate	73.1%
Posted Shifts Growth	20.0%
Churn %	10.0%
% of Accounts Referring Others	28.1%
Referrals per Referrer	1.70

Figure 11. Inputs to forecast L.A. referrals

The second line in fig. 10 is zeroes, corresponding with line 2 of fig. 11, because this line measures extra referral accounts. As this particular setup is testing for baseline scenario, no additional effect on acquisitions is expected from 2022's rate. The referral conversion rate input shows 73.1% of referral accounts in L.A. will complete a first shift. In 2023, that means 646.5 will convert and receive a bonus out of the 884 potential referrals.

After the converted referrals line, the next 3 lines in fig. 10 are for calculating legacy referrals. There were 453 referrals at prior year's end. None of them retired but 45 churned leaving 408 to continue. The next value of 1,054 represents the 408 legacy referrals plus the 646 new additions.

The line for retired nonreferrals is zero in 2023, because these are new accounts from 2022. Active nonreferrals were arbitrarily set to grow 60% to 1,350 in 2023. Adding the 1,350 with the 1,054 total referral accounts results in about 2,404 projected working HCPs in L.A. The entire process is repeated for 2024 and beyond.

3. How does the model account for churn and retirement?

Calculating churn and retirement is a bit trickier. Defining churn as accounts with greater than 50 days between shifts, the HCP data shows about 7% of L.A. referrals churned. In the model, churn was set to 10% for some degree of freedom.

Regarding retirement, the model assumes 70% retire after 3 years (backed by zero data). This category would lump all HCPs who retire, move, change careers, find alternative employment, decease, etc. For both referral and non, retirements are first seen in year 2025. Of the original 408 referrals in 2022 that did not churn, 70% retired in 2025, which is 285.

4. What were the financial results of the projections?

With acquisition projections set for the baseline bonus of $300, conversion to cash flows requires values for revenue per referred HCP and revenue per *legacy* referred HCP. Revenue from legacy HCPs assumes the same earnings rate as referrals from the first half of 2022, ie. $1,066. New referrals earned $784, calculated over all of 2022. These values initialize the first two entries in the gray column in fig. 12. Both rates decline each year to account for growth. Multiplying by the appropriate population groups projected in fig. 10 gives the total revenue earned in the third line.

	FY2022	FY2023	FY2024	FY2025	FY2026	FY2027
Revenue per Referred Account	$784	$745	$708	$672	$652	$632
Revenue per Legacy Referred Account	$1,066	$1,012	$962	$914	$886	$860
Total Referral Revenue	**$355,161**	**$940,096**	**$1,868,945**	**$2,820,787**	**$3,816,228**	**$4,586,805**
Referral Bonus	$300	$300	$300	$300	$300	$300
Total Bonus Cost	**$135,900**	**$193,942**	**$362,556**	**$479,017**	**$656,601**	**$841,970**
Total Referral Program Profit	**$219,261**	**$746,154**	**$1,506,389**	**$2,341,771**	**$3,159,627**	**$3,744,834**

Figure 12. Cash flows from L.A.'s referrals if bonus remains at $300

Accounting for cost, the bonus remains at $300 each year in line 4. Multiplying the bonus by new referrals gives total bonus cost, line 5. Finally, profit equals revenue minus cost in the last line. The sum of profits is over $11.7 million, but factoring inflation is valued at $9.53 million today.

Testing for an alternative scenario where bonus increases to $350, line 4 of fig. 12 would reflect the increase. Because acquisition numbers would likely not drop with an increased bonus, cost would be higher from the bump, resulting in an NPV under $9.53 million. Additional revenue from extra acquired HCPs must make up for the loss, in this case, 2.6%.

Conclusion

1. Are there room for improvements?

As mentioned throughout, many strict definitions, loose definitions, assumptions, and estimated values due to lack of data and resources, limit the accuracy of the model. Further research would improve the confidence level of this model's evaluations. The main limitation is likely with the revenue projections which need historical data to show how earnings change in relation to a growing workforce year over year.

2. Final thoughts?

Implementing an increase to $350 seems reasonable given the small effect needed to add profits. An even greater initial increase is possible if additional data supports that its effect will return on investment. Without this data, then starting at $350 will provide the data to evaluate further bonus increases.

Care must be taken in future evaluations to prevent acquisition growth outpacing shift supply growth if a bonus increase proves too sucessful. Future evaluations should also explore more specific localized data and study alternate data sources for overlooked acquisition factors.

Appendix

A. Model for Nashville with a $350 bonus

	FY2022	FY2023	FY2024	FY2025	FY2026	FY2027	Factors	
Referral Accounts (incl nonconverted)	83.0	134.0	288.2	484.1	802.6	1,243.2	Referral Bonus	350
Expected Referrals from Bonus Increase	0.0	3.5	7.6	12.8	21.2	32.8	Effect of Bonus Increase	2.6%
Total New Referral Accounts	**83.0**	**137.5**	**295.8**	**496.9**	**823.8**	**1,276.0**	Account Growth	20.0%
							Referral Conversion Rate	77.1%
Converted New Referral Accounts	64.0	106.0	228.0	383.1	635.2	983.8	Posted Shifts Growth	20.0%
Returning Referral Accounts	0.0	64.0	163.6	381.1	701.1	1,190.8	Churn %	10.0%
Retired Referral Accounts	0.0			40.3	107.1	250.8	Fill Rate %	66.1%
Referral Accounts Churned	0.0	6.4	10.6	22.8	38.3	63.5	% of Accounts Referring Others	41.0%
Active Referral Accounts	**64.0**	**163.6**	**381.1**	**701.1**	**1,190.8**	**1,860.3**	Total Referrals per Referrer	1.73
Nonreferral Accounts Churned	0.0			37.1	59.4	83.1		
Active Nonreferral Accounts	**53.0**	**84.8**	**118.7**	**166.2**	**232.7**	**242.7**		
TOTAL ACTIVE ACCOUNTS	**117.0**	**248.4**	**499.8**	**867.3**	**1,423.5**	**2,102.9**	**General**	
							Interest Rate	4.0%
							Degree of Freedom	2.0%
Revenue per Referred Account	$691	$656	$623	$592	$574	$557		
Revenue per Legacy Referred Account	$989	$939	$892	$848	$822	$798		
Total Referral Revenue	**$44,200**	**$129,698**	**$288,179**	**$515,754**	**$853,269**	**$1,297,965**		
Referral Bonus	$300	$350	$350	$350	$350	$350		
Total Bonus Cost	**$19,200**	**$37,115**	**$79,813**	**$134,086**	**$222,308**	**$344,323**	NPV with Changes	$1,830,641
Total Referral Program Profit	**$25,000**	**$92,583**	**$208,366**	**$381,667**	**$630,961**	**$953,642**	NPV without Changes	$1,830,555
Filled Shifts	5,720.0							
Posted Shifts	8,648.0	12,107.2	16,950.1	20,340.1	24,408.1	25,628.5		
Available Shifts per Account	73.9	48.7	33.9	23.5	17.1	12.2		
Y/Y								
New Referral Accounts		**65.71%**	**115.04%**	**68.00%**	**65.79%**	**54.89%**		
Active Referral Accounts		**155.69%**	**132.87%**	**83.97%**	**69.86%**	**56.22%**		
Nonreferral Accounts		**60.00%**	**40.00%**	**40.00%**	**40.00%**	**4.29%**		
Total Active Accounts		**112.34%**	**101.17%**	**73.52%**	**64.13%**	**47.73%**		
Posted Shifts		**40.00%**	**40.00%**	**20.00%**	**20.00%**	**5.00%**		

B. What was the unsuccessful study on fill rate effects?

Noticing the high fill rates for LA and SF, notorious for extreme costs of living, data was obtained from AdvisorSmith.com which compiles a city cost of living index. However, as seen in fig. B-1, no clear pattern emerges and other factors must explain fill rate differences amongst cities. Data of demographics statistics like customer age could prove useful, or further research into cities like HCP population estimates.

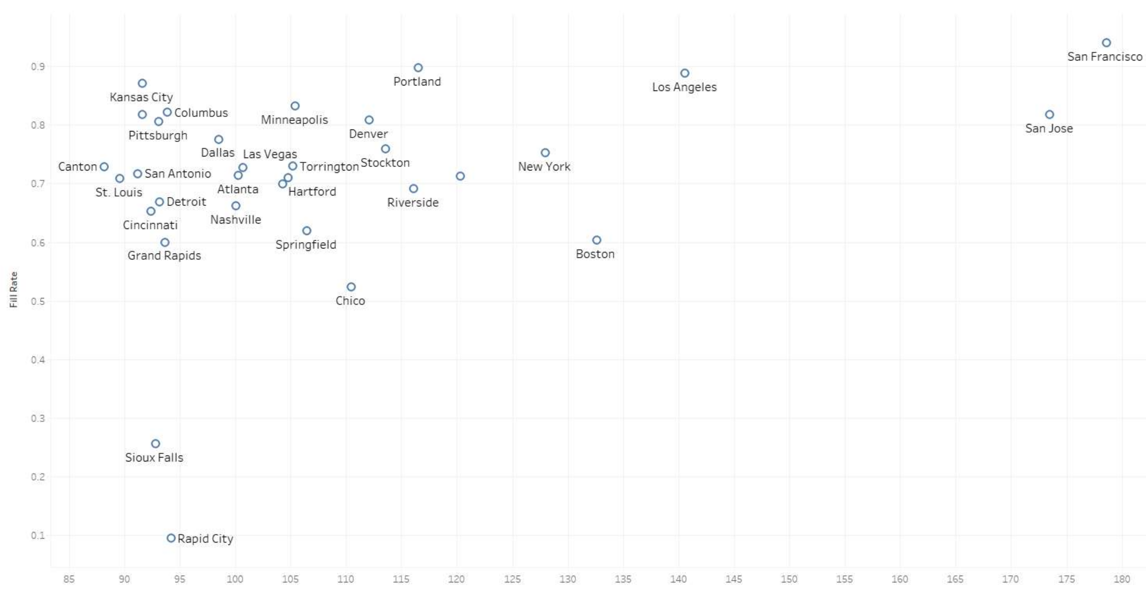

Figure B-1. Fill rate of MSA vs Cost of Living