Findings

TLDR

Are we seeing any lead quality trends over time?

• Yes, lead quality is declining. Statistical analysis shows a significant drop in closed leads (p = 0.008) and an increase in bad leads (p = 0.020) over time.

What are the key drivers of lead quality?

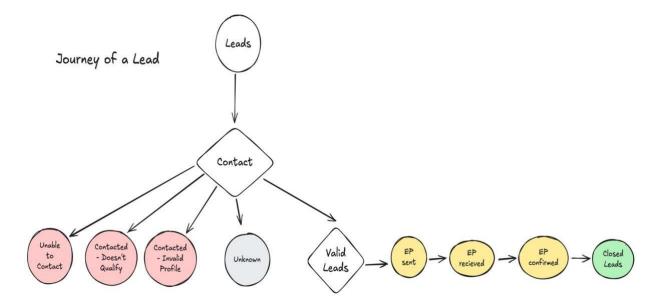
- Top Factors:
 - Ad Placement Adknowledge performs best. Landing Pages index8.html is the highest quality. Keywords "Debt" is the best, while "student loan default" generates bad leads. User Segments Users with \$10K-\$30K debt and those in CA, TX convert best.
 - o Ad Design 1DC-BlueMeter and 1DC-Head2 have the highest close rates.

What can we do to improve lead quality?

- Shift spend to high-quality sources (Adknowledge, index8.html).
- Eliminate low-performing keywords & landing pages.
- Target high-value users (debt levels, geography).
- Expand top-performing ad formats (1DC-BlueMeter, 1DC-Head2).

Context

Based on reading the problem statement, this is what I believe the journey of a lead looks like:



As stated in the question, the lead can have the following status:

- Closed Leads are the best. When discussing quality, we need to optimize for increasing the number of closed leads.
- Good Leads: EP Sent / Closed / Received are still in the conversion funnel with a possible path to closure in future and is still considered a desirable state.
- Bad Leads: No Contact / Invalid Profile / Did not Qualify are non-desirable lead traits. The business would want to minimize these to save costs & efforts.
- Neutral Outcomes: These are neither good nor bad outcomes. For this analysis, we would not optimize for this type of outcome. However, in the real world, I would like to minimize the noise.

Q1. Are we seeing any lead quality trends over time (improving, declining)? Are they statistically significant?

To track lead quality and top drivers, I will be tracking the following metrics:

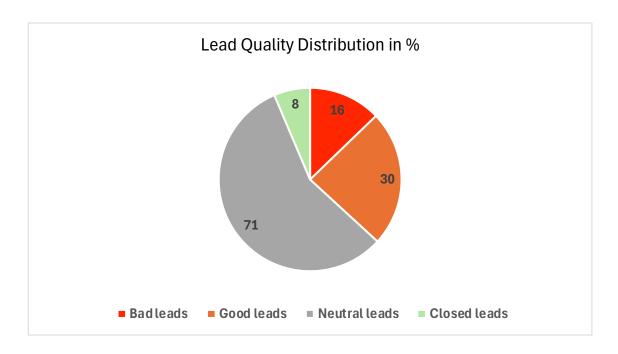
- Total Lead Count, Closed Lead % and Bad Lead %
 - The total lead count helps us identify any change in lead generation which can affect the effectiveness of the system. We want this number to grow or stay stable. In addition, we want Closed Lead% to go up and Bad Lead% to go down.
- **Weighted Score** Associates' weights to all outcomes based on relative importance. I am assuming the following scheme:
 - 5: Close Lead
 - o 2: Good Leads
 - o 0: Neutral Leads
 - -1: Bad Leads

Weighted Score = (5* Closed Lead + 2 * Good Lead + (-1) * Bad Lead) / Total Leads

Note: The weights are logically selected, but we can use other factors like cost associated and returns on closed lead to select better weights.

Additionally, I will analyze Week over Week (WoW) data. Daily data analysis is volatile and Month over Month data is sparse due to the small data sample (6 months).

Let's look at the Lead Outcome Distribution to get an aggregated view

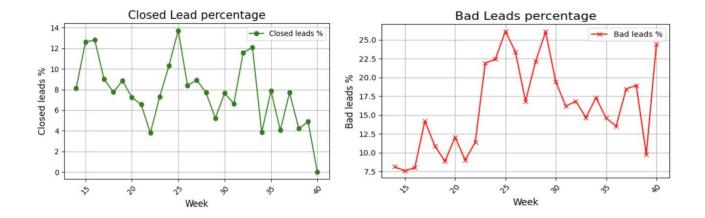


Approx 8% leads close and 16% go bad

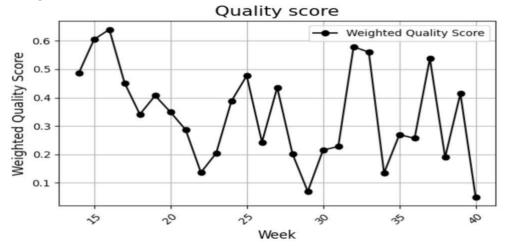
Total Leads (WoW)

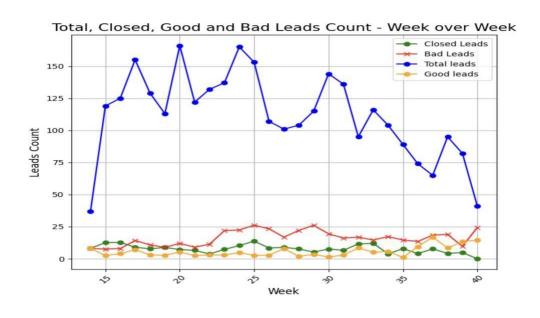


Closed Leads% (WoW) and Bad Leads% (WoW)



Weighted Score (WoW)





Statistical Analysis

I am using **linear regression** to quantify the relationship between the week and lead quality. This will enable me to perform a statistical analysis on the three parameters I have defined for measuring lead quality.

- Closed leads percentage
- Bad leads percentage
- Adjusted Weighted score

Variables used

- Independent variable Weeks
- Dependent variable Closed leads percentage/Bad leads percentage/Adjusted Weighted score

Hypothesis

- Null hypothesis There is no linear relationship between time and lead quality parameters
- Alternate hypothesis There is a linear relationship and the quality parameters are changing over time

Closed Lead percentage

```
OLS Regression Results
Dep. Variable:
                                  y R-squared:
                                                                       0.247
                                 OLS Adj. R-squared:
Model:
                                                                       0.217
                    Least Squares
Method:
                                      F-statistic:
                                                                       8.213
                                      Prob (F-statistic):
Date:
                   Wed, 29 Jan 2025
                                                                     0.00831
                          22:37:13 Log-Likelihood:
                                                                     -65.280
Time:
No. Observations:
                                 27
                                      AIC:
                                                                       134.6
Df Residuals:
                                  25
                                       BIC:
                                                                       137.2
Df Model:
Covariance Type:
                           nonrobust
                       std err
                                               P>|t|
                                                          [0.025
             10.3282
                          1.057
                                    9.775
                                               0.000
                                                           8.152
                                                                      12.504
const
             -0.1998
                          0.070
                                    -2.866
                                               0.008
                                                          -0.343
                                                                      -0.056
Omnibus:
                               0.810
                                       Durbin-Watson:
                                                                       1.480
Prob(Omnibus):
                               0.667
                                      Jarque-Bera (JB):
                                                                       0.622
Skew:
                               0.353
                                       Prob(JB):
                                                                       0.733
                               2.770
Kurtosis:
                                       Cond. No.
                                                                        29.6
```

Based on the above results, we can say that given **p-value of 0.008**, I can conclude with 95% confidence that the relationship between week and closed lead % is statistically significant, suggesting a decline in the closed lead % over time

Bad Lead percentage

OLS Regression Results						
Dep. Variable:	у	R-squared:	Ø.198			
Model:	0LS	Adj. R-squared:	0.166			
Method:		F-statistic:	6.172			
Date:	Wed, 29 Jan 2025	Prob (F-statistic):	0.0200			
Time:	22:37:16	Log-Likelihood:	-82.453			
No. Observations:	27	AIC:	168.9			
Df Residuals:	25	BIC:	171.5			
Df Model:	1					
Covariance Type:	nonrobust					
coe	f std err	t P> t [0.025	0.975]			
const 11.782	1.996	5.903 0.000 7.672	15.893			
x1 0.327	2 0.132	2.484 0.020 0.056	0.598			
Omnibus:	1.465	Durbin-Watson:	0.970			
Prob(Omnibus):	0.481	Jarque-Bera (JB):	1.349			
Skew:	0.477	Prob(JB):	0.509			
Kurtosis:	2.462	Cond. No.	29.6			

Based on the above results, given **the p-value of 0.020**, we can conclude with 95% confidence that there is a statistically significant relationship between week and average bad lead percentage suggesting an increase in avg bad % over time.

Adjusted Weighted Score

Dep. Variab	ole:	У	R-sq	uared:		0.137
Model:		OLS		R-squared:		0.103
Method:		Least Squares		atistic:		3.983
Date:	W	Wed, 29 Jan 2025		(F-statistic)		0.0576
Time:		22:37:32	Log-	Likelihood:		12.362
No. Observa	ations:	27	AIC:			-20.72
Df Residua	ls:	25	BIC:			-18.13
Df Model:		1				
Covariance	Type:	nonrobust				
	coef	std err	====== t	P> t	[0.025	0.975]
const	0.4412	0.060	7.406	0.000	0.318	0.564
×1	-0.0078	0.004	-1.996	0.057	-0.016	0.000
Omnibus:		1.689	Durb	in-Watson:		1.632
Prob(Omnibu	ıs):	0.430	Jarq	ue-Bera (JB):		1.320
Skew:		0.345	Prob	(JB):		0.517
Kurtosis:		2.166	Cond	. No.		29.0

Based on the above results, we can say that given **p-value of 0.057** I can conclude with 90% confidence that the relationship between week and quality score is statistically significant, suggesting a decline in the quality score over time

Some insights

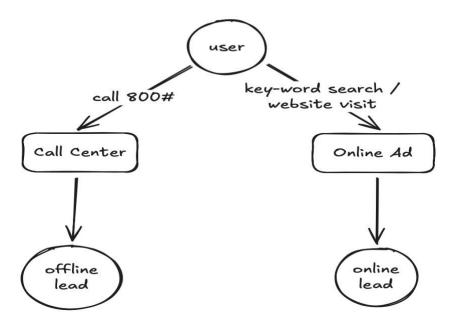
- In Week 25, both closed leads and bad leads increased, likely due to a rise in total leads.
- Week 33 was a strong month, marked by a notable increase in closed leads.
- Although bad lead quality decreased last month, closed leads remained stagnant, while good leads increased, indicating a bottleneck in the closing process
- Statistically, there has been a significant decline in closed leads and a notable increase in bad leads over time

Q2. What can we learn about the drivers of "lead quality" from this dataset? What segments - where the ad was shown, what kind of person filled out the ad, what kind of ad did they see - have differing lead quality rates?

Where was the ad shown

Leads can be generated by two methods: From Call-Center by Calling 800# or By Filling an online form.

Lead Generation



Lets deep dive into the following parameters to understand lead quality - • Publisher Campaign Name (Online vs Offline)

- Partner
- Landing Page Url
- Keywords

Aggregate quality metric for Call-Center vs Online Ad

Publisher Campaign	Total leads	Closed	Bad leads	Weighted Quality
Name	%	leads %	%	Score
Debt Reduction Call Center	9	9.59	24.35	0.369
Debt Reduction Inc	91	7.96	15.94	0.339

Insights:

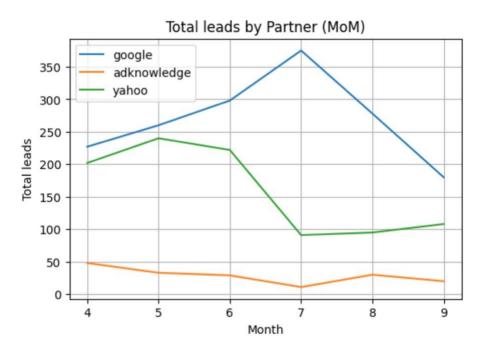
The total lead count for Online Ads (DebtReductionInc) is 91% of all leads. Only 9% leads are generated via call-centers.

The call-center leads have a slightly higher rate of closing and weighted-score.

They surprisingly have a higher bad lead rate, which could indicate a gap in

- · call center staff entering incorrect info or generating bad leads for those who do not qualify.
- · people sharing bad information

Partner



Quality Matrix

	Total leads %	Closed leads	Bad leads	Weighted Quality
CallStatusEnum		%	%	Score
Partner adknowledge	6	12.2	13.4	0.608187
Google	54	7.60	15.5	0.294808
Yahoo	32	7.72	15.3	0.362213

Insights:

Google dominates as the leading partner, contributing 54% of the total leads, followed by Yahoo. Both Google and Yahoo exhibit similar lead quality performance

Landing page URL

Landing page URL by partners

Landing Page URL	Partner	Total Leads %
Google	http://www.debtreductioninc.com/index8.html http://www.debtreductioninc.com/indexl 2. html http://www.debtreductioninc.com/indexl 1 .html	47% 4% 3%
Yahoo	http://www.debtreductioninc.com/index8.html	32%
Call center	https://callcenter.inadcoads.com/callcenter/si http://www.inadcoad.com/callcenter/signius/cal	6% 6%
adknowledge	http://www.debtreductioninc.com/index8.html	6%

Quality Matrix

	Total		Bad	Weighted
	leads	Closed	leads	Quality
LandingPageURL	%	leads %	%	Score
http://www.debtreductioninc.com/index8.html	84	8.30	14.9	0.36
https://callcenter.inadcoads.com/callcenter/signius/callcenterdri.html	6	11.70	30.31	0.40
http://www.debtreductioninc.com/index12.html	4	1.61	22.6	-0.11
http://www.debtreductioninc.com/indexll.html	3	6.97	18.6	0.18
http://www.inadcoad.com/callcenter/signius/callcenterdri.html	3	4.81	10.8	0.27

Insights:

- **Google** utilizes three landing pages, with landing page index 8 standing out not only for the highest lead count but also for generating good lead quality.
- **However**, two other URLs (index 2) appear to be driving poor-quality leads, possibly due to being redirect URLs.
- **The** call center at "https://callcenter.inadcoads" is yielding high-quality leads, whereas the one at "http://www.inadcoad.com/" shows lower quality.

Keywords

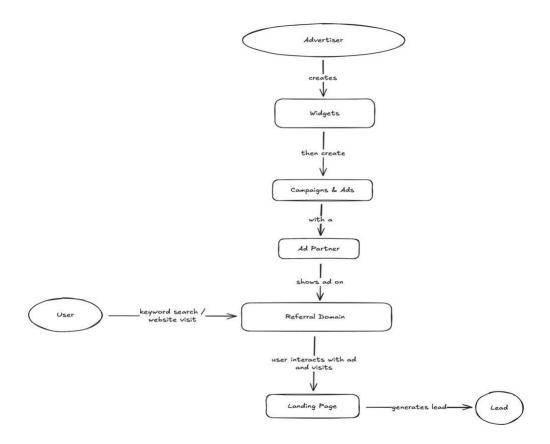
Top 10 Searched Keywords and their quality

	Total leads			Weighted Quality
Keyword	count	Closed leads %	Bad leads %	Score
debt	157	8.92	12.74	0.471338
credit card payments	104	6.73	19.23	0.201923
student loan default	51	0.00	23.53	-0.196078
loan default help	44	0.00	43.18	-0.431818
credit services	21	9.52	23.81	0.238095
debt cures	21	4.76	33.33	-0.095238

<u>Insights</u>

• **Debt** is the best performing keyword. While others like "student loan default" bring in mostly bad leads that do not close. We can optimize campaign setup by excluding these keywords

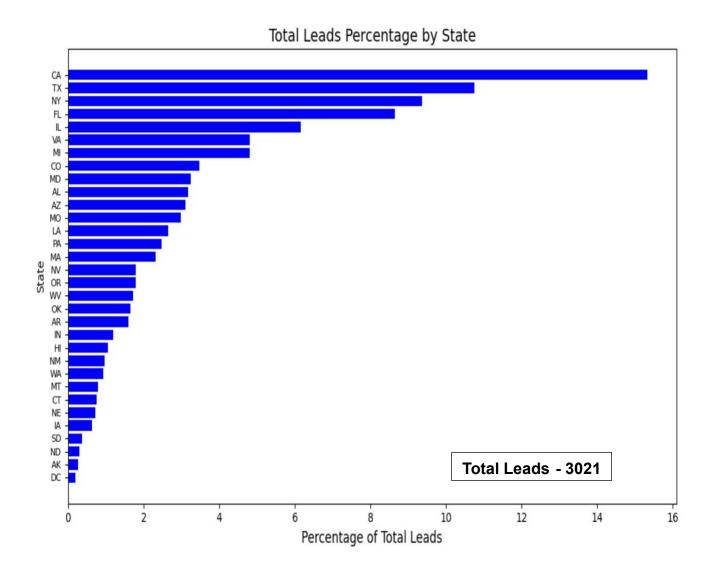
Kind of person



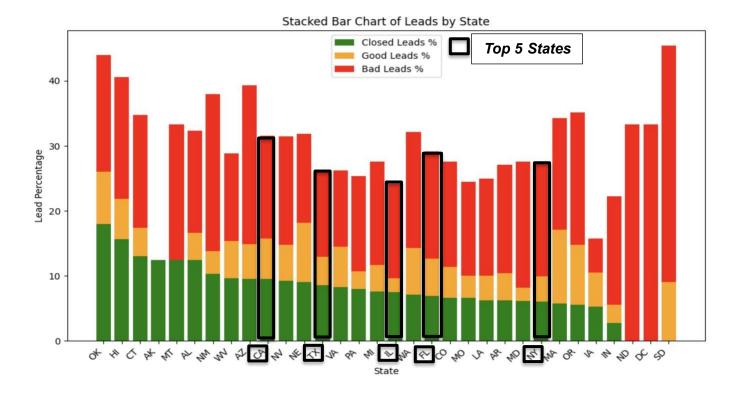
Lets deep dive into the following to understand customer and their affect on lead quality

- State
- Debt Level
- Phone Score and Address Score

Total Lead Count by state



Lead Quality by state



Insights

- CA, TX, NY, FL, and IL have the highest lead counts, which is in account with their population.
- CA and TX also show higher closed lead % than the average closed lead %, while NY and IL exhibit higher bad lead %.

Debt Level

Matrix

Debt Level	Total Leads %	Closed leads %	Good leads %	Bad leads %	Neutral leads %	Weighted Quality Score
7500-10000	15	5	2	25	68	0.04
7500-15000	9	7	4	10	79	0.34
10001-15000						
	10	12	7	17	65	0.55
15001-20000	14	9	5	12	74	0.42
20001-30000						

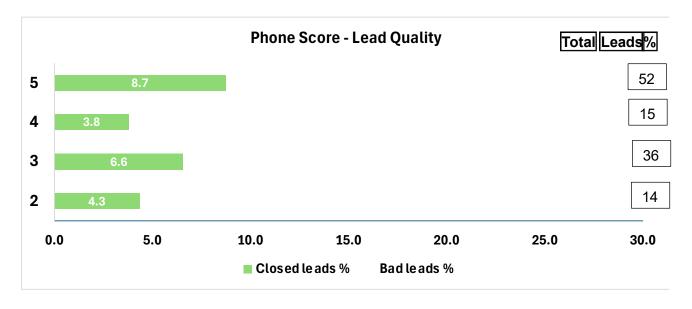
	15	9	7	15	69	0.43
30001-50000	16	8	4	17	71	0.31
50001-70000	8	9	7	14	71	0.44
70001-90000	4	14	5	12	69	0.67
90000-100000	3	10	2	14	73	0.40
More_than_100000	6	4	3	20	73	0.05

Total Leads - 3021

Insights

- Customers with debt levels between \$10,000 \$30,000 have a higher closed lead %.
- While customers with higher debt levels have lower total leads %, they still demonstrate a higher closed lead %.

Phone Score



Insufficient data for score 1

Total Leads - 1393

Address Score



Total Leads - 1171

Insights:

 Both phone score and address score show that their higher values are associated with better lead quality

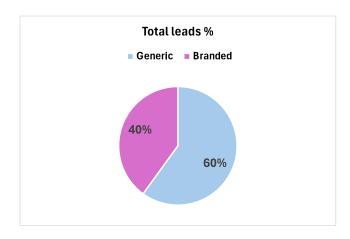
What Type of Ad

Lets deep dive into the following parameters to understand lead quality

- Logo Type
- Widget Name (1DC (1 page) vs 2DC (2 page) and Design Type

Logo Type

Generic vs With Brand Logo



Campaign Type	Closed leads %	Bad leads %
Generic	8.320	16.419
Branded	7.794	15.755

Insights:

The split between total leads generated from generic ads and those with brand logo is 60 / 40.

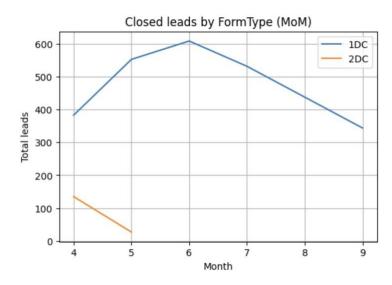
- Surprisingly the closed lead percentage for Generic ads is higher.
- Since there are multiple widgets designs it is not fair to use the above to decide which is better. We should look at equivalent designs where one has branding and other doesn't to make this decision.

1DC (1 page) vs 2DC (2 page)

				Weighted
Form Type	Total leads %	Closed leads %	Bad leads %	Quality Score
IDC	95	8.14	16.33	0.34
2DC	5	7.40	12.9	0.33

Insights:

- The 1DC form makes up for 95% of the total ad generated lead. This can be attributed to potential drop-off of customer between the two form pages.
- The closed lead % is higher for 1DC vs 2DC, but so is the Bad Lead% as an easy UI might invite more people who are just clicking for fun/curiosity or are non-qualifying.
- 1DC format is better in this case as it is generating a much higher number of leads, we can see 2 DC was discontinued after two months from chart below.



Design Type

Design Name	Total leads %	Closed leads %	Bad leads %	Weighted Quality Score
1DC-CreditSolutions	37	7.8	15.7	0.34
1DC	21	9.2	19.0	0.37
1DC-white	14	7.3	15.8	0.27
1DC-yellowarrow-blue	8	6.5	21.1	0.25
1DC-yellowarrow-dark	4	7.4	18.5	0.26
1DC-BlueMeter	3	14.1	4.3	0.68
1DC-Head2	3	12.4	9.0	0.60
2DC-BlueMeter	3	6.9	10.3	0.38
1DC-Head3	2	5.3	9.3	0.20

Insights

- We can see from comparison of different designs that the 1DC-CreditSolutions and 1DC (generic) are biggest in-term of generating leads and have overall decent lead quality.
- The two widgets 1DC-BlueMeter and 1DC-Head2 have high closing rate and overall score.
 They also have a low bad rate percentage. It is worth investigating those two designs to see what they are doing right. We also need to investigate why their share in overall lead % is small.

Q3 If the advertiser says they will increase our CPL by 20% (i.e., \$30 to \$33) if we increase our lead quality by 20% (i.e., from 8.0% to 9.6%), do we see any opportunities to do that here? What kinds of things could we do?

1. Optimizing Ad Placement and Partners

- Call Center vs. Online Ads: Call center leads have a slightly higher closing rate but also a
 higher bad lead rate. Improving call center data quality (e.g., better screening, verification
 processes) could enhance lead quality.
- Partner Selection: Ads from Adknowledge have the highest weighted quality score (0.608), significantly outperforming Google (0.294) and Yahoo (0.362). Increasing the budget for Adknowledge ads could improve lead quality.

2. Refining Landing Pages

- **Best Performing Landing Page:** index8.html performs best across platforms. Prioritizing traffic to this page while discontinuing or modifying lower-quality pages (e.g., index12.html, index11.html) can improve conversions.
- Call Center Landing Page Discrepancy: One call center URL (callcenter.inadcoads.com) produces high-quality leads, while another (inadcoad.com) performs worse. Investigating and standardizing best practices across call center pages may help.

3. Keyword Optimization

- **High-Performing Keywords:** "Debt" has the highest lead quality (8.92% closed, 12.74% bad, weighted score 0.471). Investing more in this keyword could increase quality.
- Poor-Performing Keywords: Keywords like "student loan default" (0% closed, 23.53% bad) and "loan default help" (0% closed, 43.18% bad) should be excluded or reduced in bidding.

4. Targeting Higher-Quality Users

• **Debt Level:** Users with debt levels between \$10,000 - \$30,000 show the highest closed lead rates. Adjusting targeting to focus on these segments (rather than very high or very low debt levels) could improve lead quality.

• **Geographic Focus:** CA and TX have above-average closed lead rates. Increasing ad spend in these states while reducing investment in states with high bad lead rates (like NY, IL) could help.

5. Ad Design and Format Adjustments

- **Branding:** Surprisingly, **generic ads** (8.32% closed) outperform branded ads (7.79%). Testing similar designs without branding for better performance could be an option.
- Best Performing Ad Designs: 1DC-BlueMeter (14.1% closed, 4.3% bad, 0.68 weighted score) and 1DC-Head2 (12.4% closed, 9.0% bad, 0.60 weighted score) have the best performance. Investigating what makes these successful and replicating their features in other designs could improve overall lead quality.
- Form Type: The 1DC (one-page) form has a higher closed lead rate (8.14%) than 2DC (7.40%), despite more bad leads. It should remain the primary form, but small adjustments to filter out low-quality leads may help.

Action Plan to Increase Lead Quality by 20%

- 1. Shift ad spend to high-performing partners (Adknowledge) and optimize Google/Yahoo ad targeting.
- 2. **Redirect traffic to high-performing landing pages** (index8.html, callcenter.inadcoads.com).
- 3. **Exclude low-quality keywords** and increase bids on "debt" and other high-performing terms.
- 4. Focus ads on users with \$10,000 \$30,000 in debt and in high-performing states (CA, TX)
- 5. Expand successful ad designs (1DC-BlueMeter, 1DC-Head2) and test generic branding.
- 6. **Improve call center processes** to filter out unqualified leads before submission.

By implementing these optimizations, the lead quality should improve, making the proposed CPL increase to \$33 worthwhile.