FINDINGS REPORT 2022

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Introduction

Digital Factory has deep data analytics expertise leveraged by CVSHealth Specialty to identify critical results that will generate recommendations for increasing conversion rates of digital adoption.

Currently, around 50% of patients are registered for a CVSHealth Specialty Digital Account. However, Digital Factory understands that CVSHealth Specialty's goal is to achieve an activation within the 60% range for digital usage.

Digital Factory is passionate about delivering high-quality results. Our passion and expertise were leveraged to assist CVSHealth Specialty in driving identifying variable data analysis to CVSHealth Specialty digital channels. After having done an internal data science review, CVS stakeholders wanted a further investigation of Call Center metrics & campaigns to lift EBIT by $1-4MM by boosting Digital Engagement and reducing incoming call volume.

After completing a data science approach and methods audit, we found problematic assumptions and calculations in the handoff materials. With database access, we determined that longitudinal studies of these call center metrics were necessary for generating actionable intervention plans.

In this report, you will find out detailed analysis, methodologies, findings, and recommendations.

Digital Factory has also outlined a series of outstanding items that should be explored to enhance efficiency and effectiveness in digital engagement.

1. “Toggler” Longitudinal Analysis

After initial patient-level engagement exploration, two groups of patients are identified. The first group is patients who are constant (month to month within 2021), engaged, or reached where there was little to no change in their monthly digital engagement behavior. The second group is patients who toggle between engaged vs. reached.

These longitudinal analysis findings are specific for the **toggler patients.**
Digital Factory leveraged natural language models to assign individual patient history notes into 100 different note summarizations (see appendix).

Digital Factory then conducted a longitudinal analysis (with monthly granularity) to examine the correlation between note topics and engagement. The following are the findings.

Analysis 1A

Digital Factory uses an NLP (Natural Language Processing) model to cluster Patient Note data from the Patient History Table into **topics.**
These topics are represented by a data state vector with values such as

- *‘Paid $7 COPAY FOR EPI AND $5 FOR REMICADE.’*
- *‘User: DSPARCS Method of Payment: CREDIT CARD Authorization Number’*
- *‘Intervention Name: Adherence Monitoring with Organization: CVS Specialty created. Intervention Name’*

We then ran correlations to determine the relationship between digital engagement and these topics. The top 50 most correlated topics were then categorized further, into System Keywords, with examples such as

- *‘Adherence’*
- *‘Silverlink’*
- *‘Clinical Request’*

Correlations across topics are then weighted and aggregated against System Keywords to provide a System Keyword Importance Score. This **System Keyword Importance Score** provides an index that is aggregated by weighting each topic correlation:
(System Keyword Correlation) = (Individual Topic Correlation) * (Individual Topic Event Count)
So, for example, with a system keyword of ‘Copay,’ we have two topics that have negative correlations. The weighted correlations are summed to provide an aggregated **System Keyword Importance Score** value of -841.7963403

System Keyword	Topic Label	Correlation to Digital Engagement	Number of Patient Events	Weighted Correlation
Copay	To determine if your Humira is eligible for a cost reduction, please click this link	-0.030061067	16752	-503.5829944
Copay	Paid $7 COPAY FOR EPI AND $5 FOR REMICADE	-0.015203333	22246	-338.2133459
				-841.7963403

System Keywords	System Keyword Score
Inbound Calls	-5912.949963
Silverlink	-2993.337712
Enrollment	-2220.815243
SPRx	-1408.958879
Adherence	-1056.507274
Copay	-841.7963403
Referral	-836.6664282
Match to Full	-340.99176
Clinical Request	-262.3250295
First Fill Tracker	-249.9285652
Disability Report	-212.1995721
System Update	-148.2458316
Outbound Message	-71.07636805
Outreach	109.83364
Reminder	137.4121011
Billing	154.111116
CAP	284.2236282
Clinical Message	311.396967
Insurance	476.5322447
Delivery	480.4559675
Refill notification	581.0945345

Message	639.2468059
Payment	2394.357359
Digital Order	18118.33364

Analysis 1B

An alternative set of longitudinal analyses applied to the existing summary text column of the note history table revealed similar findings:

NLP-Generated Patient Note Summary	Correlation to Engagement
<SM><Re-Confirm Delivery (SM)>	0.127581
<SM><SE0003 (NSM)>	0.128069
Push Digital Rx Refills for CVS Specialty Patients	0.129304
<SM><SE0038 (NSM)>	0.134064
<SM><SE0151 (NSM)>	0.142545
<SM><Refill Too Soon (SM)>	0.152131
FF_IND_bool	0.154818
SUCCESSFUL PRESCRIBER CONTACT ATTEMPT VIA ERX	0.161781
<SM><ADHMNTR0007 (NSM)>	0.168091
toggled	0.294894
<SM><Refill Reminder - Final Attempt (NSM)>	-0.030696
IBC regarding TALTZ	-0.031094
IBC regarding OTEZLA	-0.031363
<SM><ADHMGT0002 (NSM)>	-0.031828
IBC regarding COSENTYX SENSOREADY PEN	-0.032156
IBC regarding STELARA	-0.038621
IBC regarding DUPIXENT	-0.041562
<SM><Final Refill Reminder - Attempt 1 (SM)>	-0.046570
Allergies section of Clinical Request not complete	-0.050633

New Intervention Created	-0.071133
ORDER MESSAGING RESULT	-0.075412
Patient transitioned to SPRx	-0.107110

Specifically, **First Fill Tracker** and a subset of **Adherence** programs are causing very positive engagement with targeted patients.*

TAKEAWAYS

Patients with **inbound calls, Silverlink, and enrollment interactions** have the most negative System Keyword Scores, which correlate very negatively with Digital Engagement (one goes up, the other goes down). Therefore, this may be the preferred method of checking the status, refilling, and payment for these subsets of patients.

New **patient-related enrollment events** are significantly negatively correlated with engagement.

Digitally formatted outreach, such as delivery notifications, refill reminders, and incoming outreach call notifications, are significantly positively influencing engagement. In addition, messages/Emails with a **secured link response** built within the message are causing digital engagement.

Patients with non-digital interaction behavior are driven by their previous interaction channels with CVS. Interventions and ideas based on the above findings are

- Attempt to route the routing IBC, and Silverlink calls that have resolved positively (e.g., bill paid successfully) into digital form.

OUTSTANDING ITEMS

Valuable enhancements would include:

- **Performance updates** to NLP summarization and topic categorization (lemma analysis, fuzzy matching).
- **Departmental discussions** to understand the processes behind the key correlations between enrollment and Silverlink interactions.
- **Patient security confidence** campaigns to determine how deeply patient confidence in security affects Digital Engagement.

2. Updating The Digital Engagement Model - V2

A review of the existing engagement model data and feature importance uncovered that the data leakage between the train and test split is highly likely in the internal autoML framework service, DataRobot. Therefore, the motive of the V2 engagement model is to retest the original model features set grouped at a patient level and remove data leaks caused by duplicates.

Due to duplicates introduced by unsound SQL joins, the previous engagement ratio was mentioned to be close to **1:1** between Digitally Engaged vs. Reached. Without duplicates, this ratio is revealed to be much closer to 66/33, or a **2:1 ratio** between Digitally Engaged vs. Reached.

The V2 Digital Engagement Model aims to approximate mostly static features and their influence on the engagement. With the V2 engagement model, each patient can be scored for how likely they are to be engaged based on their featured patient profile. Opportunity sizing can then be estimated based on the Expected Engagement Score vs. the Realized Engagement Score.

Patient Level Aggregation

Patient-level modeling requires features to describe patient characteristics over multiple fill cycles. While most patient features are static, some features can potentially change and update during the length of time of the 2021 engagement model dataset. Therefore, each original patient feature is aggregated into fill with the feature count value normalized by each patient's total number of fills.

For example, if a patient has 3 fills total in 2021, filled at **Pharmacy A** 1 time and **Pharmacy B** 2 times, the encoded location feature value for **Pharmacy A** location is 1/3 and 2/3 for **Pharmacy B**.

This aggregation is also applied to the target variable. This allows patient features and engagement metric-dependent variables to be invariant to several fills.

Target Variables

Engagement is a composite metric calculated on fill level based on patients' digital activity and the fill order itself being digital. While engagement can be modeled directly through experimentation, it has been proven it is more accurate to infer patients' order status than engagement status.
A blend of two-level models is used to predict engagement more robustly. For example, base **Model_10** predicts fill engagement status, and base **Model_11** predicts user digital interaction engagement status.

*Different Adherence campaign IDs are either very positively correlated to engagement or negatively correlated. Details on why this is to be investigated.

Model_00 uses the output probability of the previous two dependent variables as a feature along with the original feature set to predict the combined engagement metric. This has been shown to **improve the accuracy** of a down-sampled equal split between engaged and reached 4-5%.

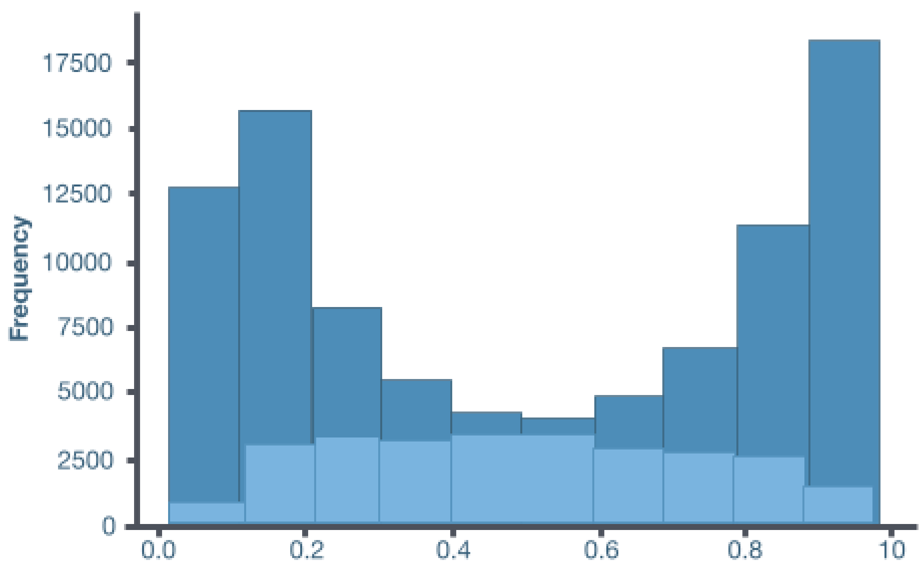
Some patients are **Partially Engaged.** An example is when a patient is Digitally Engaged in 1 out of 3 fills. These examples are filtered out from the training and test set as they are driven by external events such as previous digital engagement campaigns and adherence campaigns.

Train Test Split

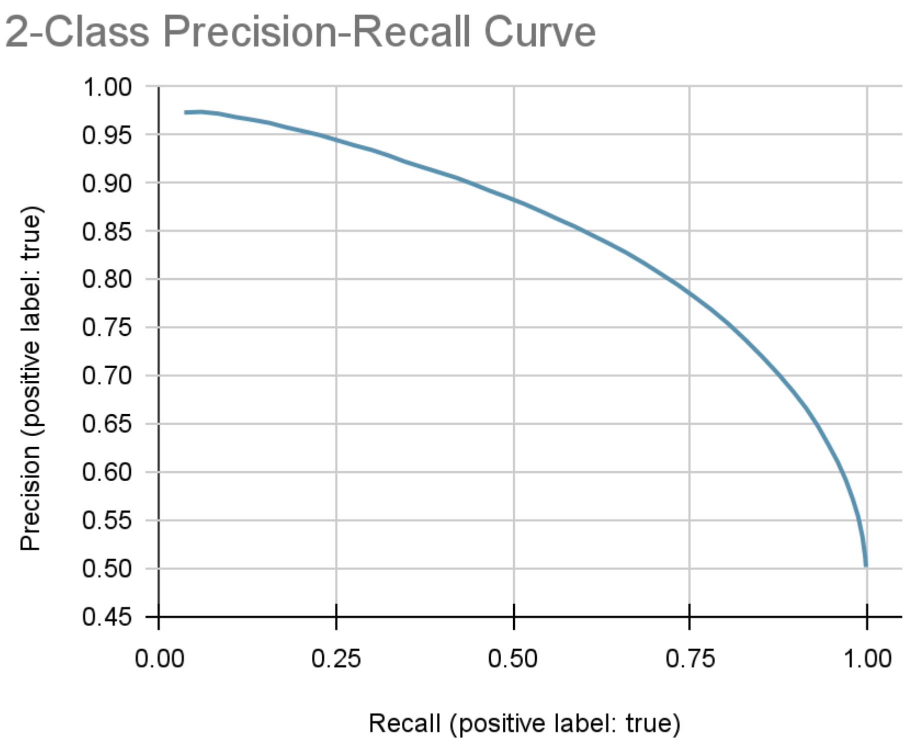
Digital Factory implemented the train test split methodology to test how well the V2 generalized engagement is through its original set of features; 2 train split strategies are applied in 4 quadrants of their combinations. The first strategy is randomly split on the patient's unique id. This tests the model across patients during the same period.

The second strategy is to split the train and test in time. The model is trained on partial patient ids with a fill dataset from 2021 and tested in 2022 up to July. The initial model result showed 76% and 75% train/test accuracy at a balanced target variable ratio of 50/50 for the cross-patient split. 74% accuracy when applying the same model in future 2022 months. 70% accuracy on patients that were not in training set during the months of 2022.

Opportunity sizing based on the expected engagement vs actual engagement ratio over 2022 up to July is used to identify patients that are not currently engaged but have an engageable profile based on their static features such as age, drug class, education, and communication preferences. Below are estimated two brackets based on a delta of .5 and .7 delta in expectation.



Evaluation metrics: Number of examples with correct label prediction in light blue and wrong prediction dark blue vs output probability of label being positive (digitally engaged)



GradientBooster (API = 0.85)

Evaluation metrics: Precision Recall score at various prediction thresholds. Bigger area under the curve, better performance.

Digital Factory used the V2 Engagement Model to estimate the expected engagement probability based on previously engineered and referenced features. Each patient who is eligible for digital engagement is evaluated. Those patients that are mostly reached but were identified by the model as highly engageable are chosen with a **Low** (.5) and **High** (.7) tolerance threshold to estimate higher and lower bound of possible monetary savings given CVS's estimate of a $95 reduction in cost to serve when 100 refills are converted to digitally engaged.

With a **High** tolerance threshold for 2022 Jan-June

- the number of patients in the conversion candidate pool is 24148
- the number of fills in conversion candidate pool is 99546.7
- savings based 100 fills saving $95 is **$104,78**

With a **Low** tolerance threshold for 2022 Jan-June

- the number of patients in conversion candidate pool is 52085
- the number of fills in conversion candidate pool is 195630.65
- savings based 100 fills saving $95 **$205,927**

TAKEAWAYS

The existing CVS Digital Engagement model had multiple areas needing improvement for accuracy, ranging from optimizations in approach due to usage of the internal autoML tool Data Robot to updates to database queries to de-duplicate data correctly.

After correcting these issues, the updated model now shows us that there is roughly a **2:1** ratio of Digitally Engaged to Reached. In contrast, the previous analysis concluded a **1:1,** indicating that there are more digitally engaged specialty patients than initially calculated.

These updated analyses give us a range of **$104,78 to $205,927** in YoY savings with converting refills to digitally engaged.

OUTSTANDING ITEMS

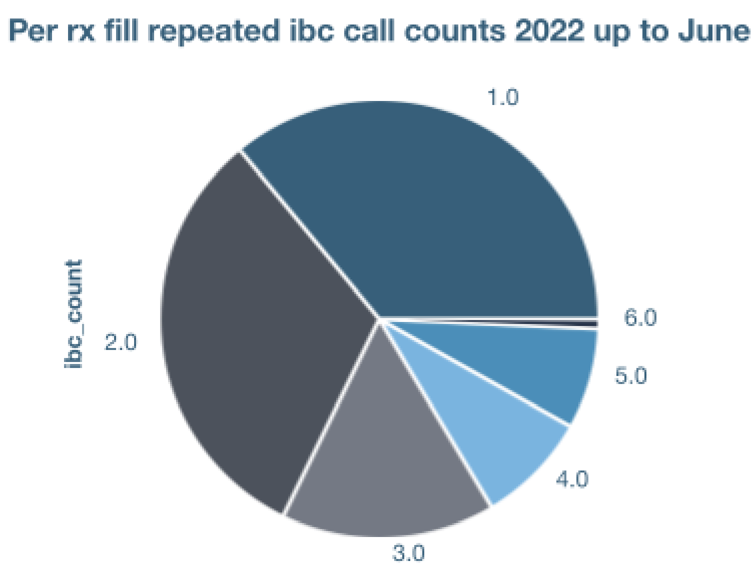
Valuable enhancements would include:

- **Performance updates** to include GPI codes and other patient attributes not available currently.
- **Procure a deeper specialty dataset** to include non-sandboxed records for higher precision and accuracy.

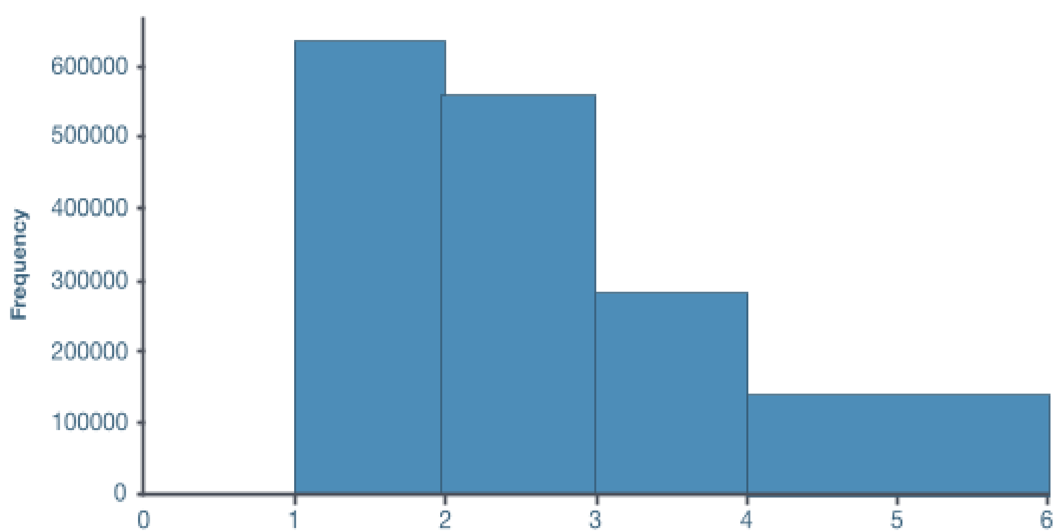
3. Duplicated IBC Call

Within the Communication Summary database table, CVS has records of incoming refill calls with its associated Patient ID, Rx number, and refill number. A preliminary analysis revealed **multiple** incoming calls to refill over the phone regarding a **single** refill number.

For each patient, Rx number, and refill number, the most optimal number of inbound calls labeled with reason code ‘Ready for Refill’ is one single call. However, after analyzing the communication summary table, it has been observed that approximately 50% of refills required more than one inbound call.

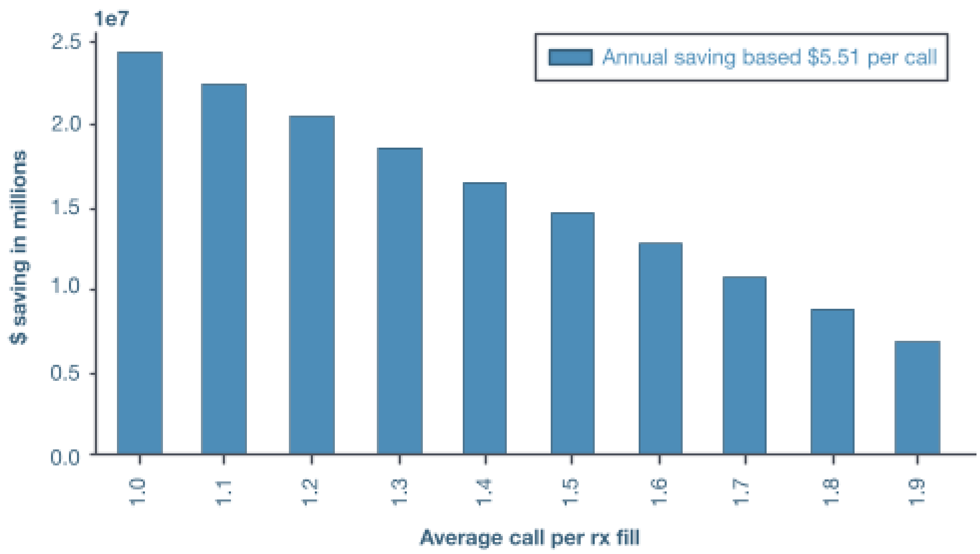


Digital Factory calculated the potential saving from inbound calls for refill purpose with increment of average number of inbound calls per fill increments .1 calls. Example of 1.1 calls per fill: out of 100 refills 10 refills took 2 inbound calls 100 refills took 1 inbound call. (2*10 + 1*90) / 100 = 1.1



This chart shows number refill counts for particular patients, Rx number, and refill number vs number of inbound calls.

For every fill, a patient would ideally call at most once. But a high number of patients call more than that. Previous analysis has shown that it costs an average of $5.51 per inbound call. In the best-case scenario, if every patient calls only once per refill, the savings would amount to **$2.4 million over the sampled specialty patients**.



TAKEAWAYS

Individual Rx numbers often have more than 1 IBC (inbound call) per month. The causes of this could have readily available solutions to reduce this frequency significantly.

Even a reduction to 1.7 calls a month amounts to **$1 million** in YoY savings over the sampled specialty patients. If able to bring that down to 1 call per month, the YoY savings will jump to **$2.4 million** for the sampled group.

OUTSTANDING ITEMS

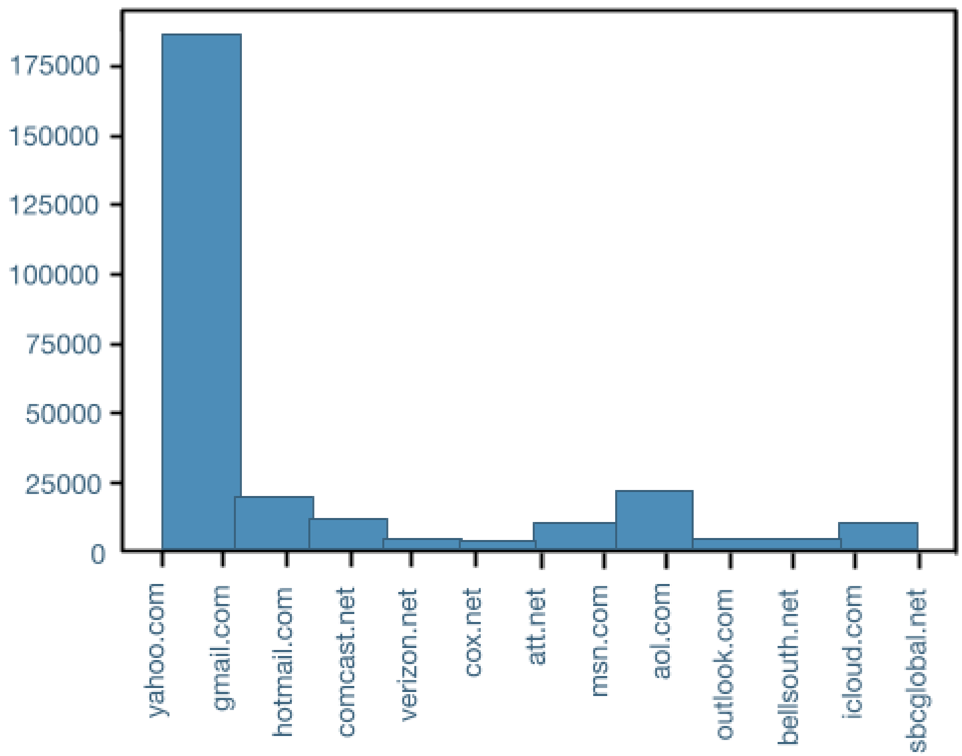
Valuable enhancements would include:

- **Quantifying** the true specialty patient population size, outside of the available sandbox data.
- **Deeper dataset access** utilizing our NLP solutions and other tools to uncover reasons for such a high frequency of duplicate inbound calls.
- **Departmental discussions** to understand the inbound call process and potential causes for duplicate inbound calls.

4. Email services used to receive the Ready to Refill Notifications

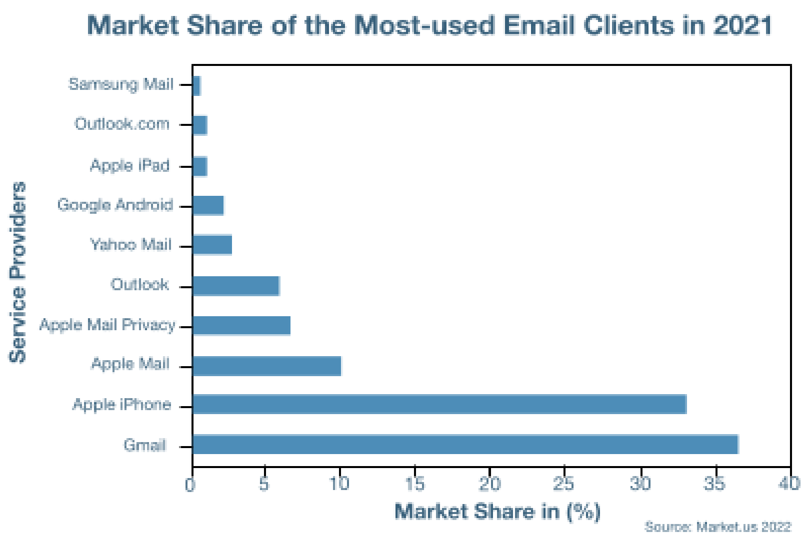
67.8% of sampled specialty patients use Yahoo.com as their primary email address to receive RFR (ready for refill) notifications. This is a **very** high number when compared to the next highest, Gmail, at **6.8%**.

X-axis: Email Provider name.
Y- axis: The number of patients using a given email provider.

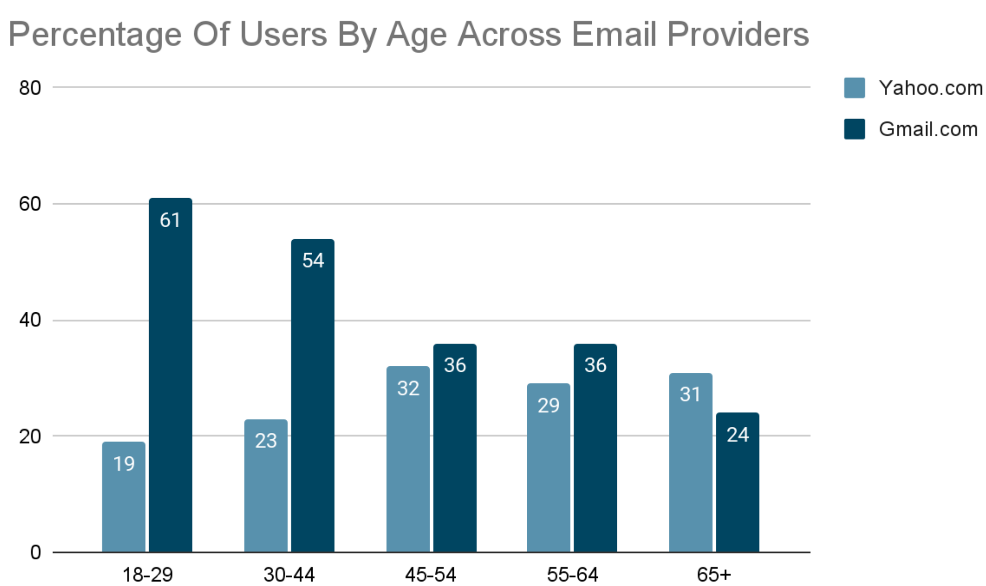


This is an **incredible** deviation from current 2021 statistics on email provider usage, which shows Gmail and Yahoo normally taking completely a completely opposite relationship:

X-axis: Market Share.
Y- axis: Email Provider name.



Further demographics reveal that the majority of yahoo.com email users are 55+ (60%), and the vast majority are 45+ (92%). Whereas the majority of gmail.com users are within the 18-29 bracket (61%).



sources:
https://earthweb.com/yahoo-mail-users
https://www.statista.com/chart/9937/the-gmail-yahoo-mail-age-divide

TAKEAWAYS

Digital signatures of age and demographics, such as yahoo.com email users, can corroborate the basic assumptions of a model. This also strengthens the approach to generate further proxies for additional user-generated features that are also highly correlated to age (i.e., income, leisure time, diet, etc.).

OUTSTANDING ITEMS

Valuable enhancements would include:

- **Validating** the statistical findings and their correlation to the age population of the sample group.
- **Generating** additional patient demographic features, extrapolated from their email account preference.
- **Reporting** the correlations between email provider and Digital Engagement status.

5. Calls vs Notifications

Digital Factory used an NLP (Natural Language Processing) algorithm to cluster all available sent communication notes regarding RFR (ready for refill) notifications conducted via email or SMS.

These sent communication notes were then processed and made into a data frame to extract information. We also discovered another collection of notes detailing when the sampled specialty patients called CVS regarding the notifications they received afterward.

After processing and cleansing the dataset, we performed an inner join on the Patient ID to generate a new table for the analysis.

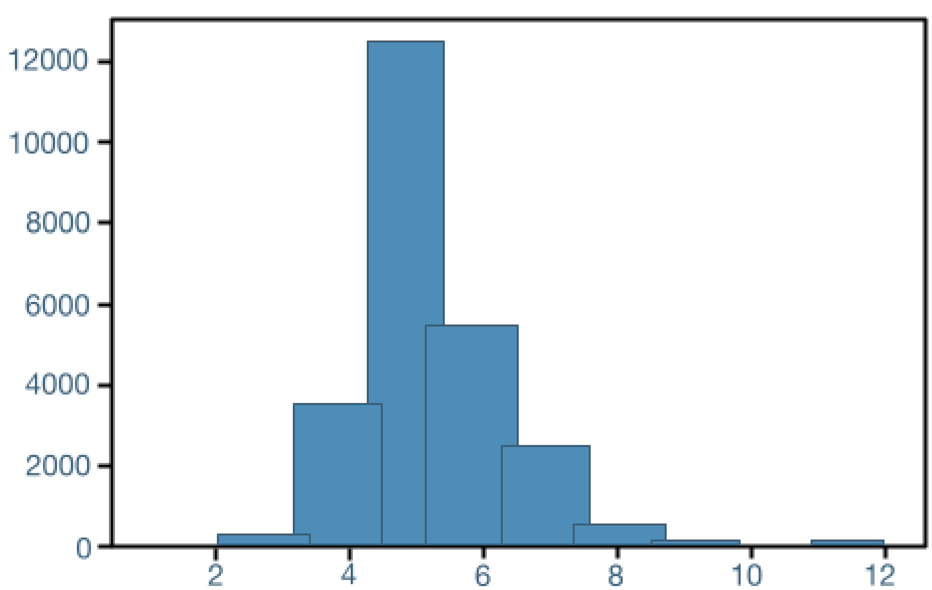
The following chart shows the latency between when the ready-to-refill notifications were sent via text/email and when people called CVS regarding those notifications.

Ready For Refill Notifications Sent - Hour Of Day

X axis: Hour of day the notification was sent.
Y axis: Number of Ready For Refill notifications (email/SMS) sent during that hour.

```
df_test[ 'hour_RFR_Noti ' ] . hist( )
```

<AxesSubplot: >

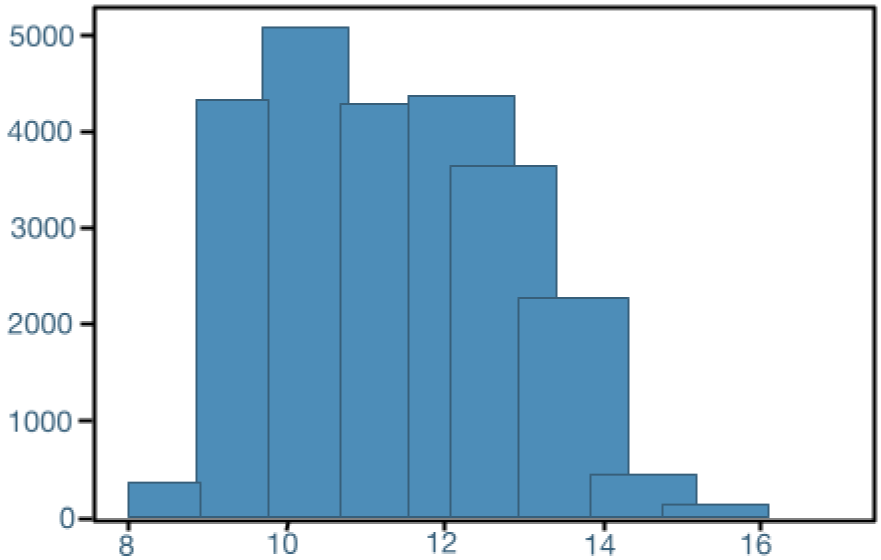


Inbound Refill Calls - Hour Of Day

X axis: hour the call was placed
Y axis: Number of inbound calls

```
df_test[ 'hour_called' ] . hist( )
```

<AxesSubplot: >

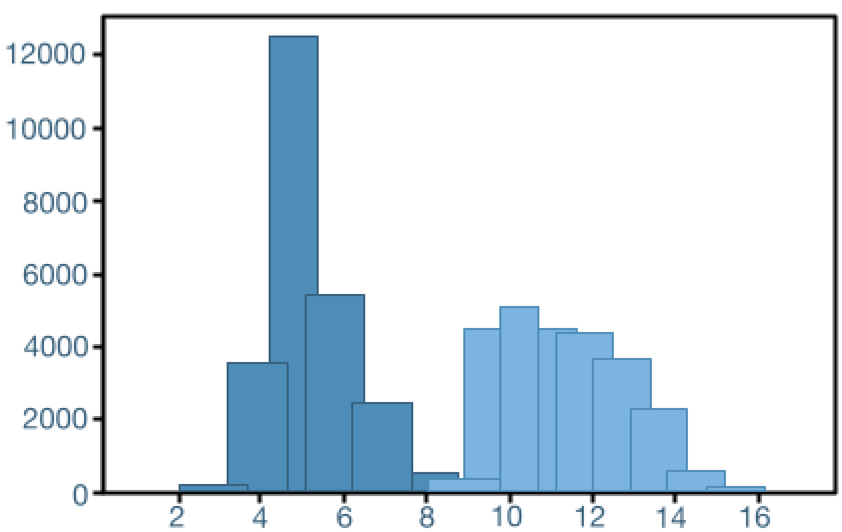


Notification To Inbound Call Latency - Hour Of Day

X axis: Hour of day a notification was sent vs hour a call was placed.
Y axis: Number of calls/notifications during that hour.

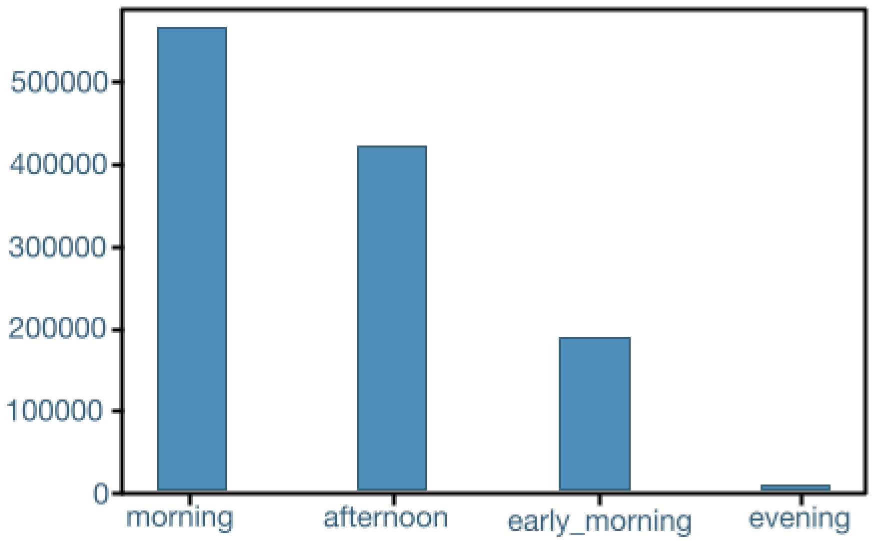
```
df_test[ 'hour_RFR_Noti' ] . hist( )  #blue
df_test[ 'hour_called' ] . hist( )  #orange
```

<AxesSubplot:>



CVS also sends out a refill notification to patients to inform them that an order is ready to be refilled. Patients need this information to assess their refill needs accurately. Unfortunately, most (98.72 %) of "ready to refill" notifications are sent at times that may result in a massive influx of calls in the morning.

X axis: Phase of day.
Y axis: Number of inbound calls.



The dataset show that:

- 17,500 calls occurred from 9am – 1 pm.
- 6,600 calls occurred from 8am-9am and from 1pm- 4pm.

There are very few calls regarding the ready to refill notifications in the evening.

TAKEAWAYS

Whether by design or process, Ready For Refill notifications are primarily sent overnight for a given patient. The average IBC patient then calls the following morning about this fill[s].

Call center preparation and optimization could readily result in cost savings from anticipated wait time reduction and call center resource allocation.

OUTSTANDING ITEMS

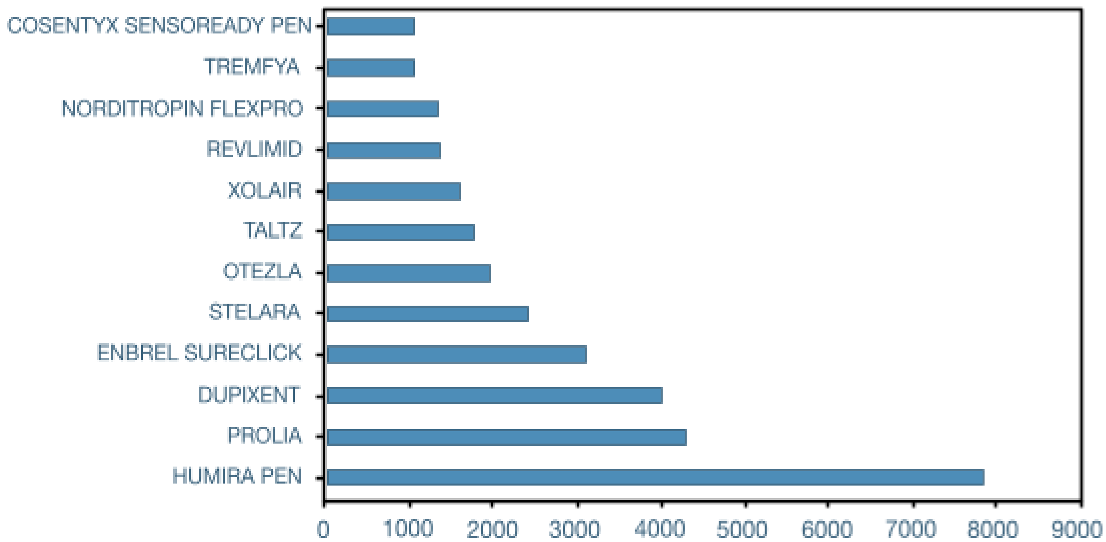
Valuable enhancements would include:

- **A trailing call volume analysis** to understand on a per-patient basis what is the most likely response time; for instance, if Patient A received an RFR message at 7 am, we count the number of subsequent IBC calls from Patient A at all following hours.
- **Generate** a machine learning model to calculate, given a patient characteristic, when the patient is the most likely to call back.
- **Utilize** NLP techniques to extract similar insights for other existing communication note collections.

6. Inbound Billing Calls

Inbound calls tagged as billing were investigated as well, with several particular drugs standing out.

X axis: The number of calls regarding a drug.
Y axis: Drug name.



Billing IBC Calls	note_smry_txt	% of total
IBC regarding HUMIRA PEN	7854	9.533057
IBC regarding PROLIA	4306	5.226553
IBC regarding DUPIXENT	3999	4.853921
IBC regarding ENBREL SURECLICK	3101	3.763943
IBC regarding STELARA	2423	2.940998
IBC regarding OTEZLA	1964	2.383871
IBC regarding TALTZ	1763	2.139901
IBC regarding XOLAIR	1599	1.94084
IBC regarding REVLIMID	1355	1.644677

IBC regarding NORDITROPIN FLEXPRO	1335	1.620401
IBC regarding TREMFYA	1052	1.2769

TAKEAWAYS

For Billing, patients call CVS regarding **HUMIRA PEN** the most, followed by **PROLIA** and **DUPIXENT**.

OUTSTANDING ITEMS

Valuable enhancements would include:

- **Departmental discussions** to gather domain knowledge as to why so many people call regarding the billing of these three particular drugs; this could be as simple as having a more significant percentage of patients on these drugs or inherent issues with billing these drugs.

7. Final Recommendations

We recommend leveraging the newly created engagement model V2 to identify conversion candidates for future digital engagement campaigns. This resulted in $200,000 - $400,000 annual savings for 2022. These results and improvements can be reutilized for 2023 and onward.

We would further investigate the "reached" patient population and identify detailed reasoning for patients to call in multiple times for refill transactions. This can generate a process and campaign for repeated call reduction. Reducing repeated/duplicate calls for the same refill number down to 1.1 - 1.3 calls per refill from the current spread of 2-6 calls per month can result in savings of **~$2.4MM dollars per year**.

Additional investigations into the following areas also have indications for substantial savings:

- **Departmental discussions** to gather domain knowledge as to why so many people call regarding the billing of essential prescriptions (HUMIRA PEN, PROLIA, and DUPIXENT); this could be as simple as having a more significant percentage of patients on these drugs or inherent issues with billing these drugs.
- **Funneling IBC and Silverlink calls** that have resolved positively (e.g. bill paid successfully) into digital form.
- **Patient security confidence** campaigns to determine how deeply patient confidence in security affects Digital Engagement.

To facilitate these further investigations, the current outstanding items will need to be addressed:

- **Performance updates** to NLP summarization and topic categorization (lemma analysis, fuzzy matching).
- **Utilize** NLP techniques to extract similar insights for other existing communication note collections.
- **Deeper dataset access** utilizing our NLP solutions and other tools to uncover reasons for such a high frequency of duplicate inbound calls.
- **Quantifying** the true specialty patient population size, outside of the available sandbox data.
- **Validating** the statistical findings and their correlation to the age population of the sample group.
- **Generate** a machine learning model to calculate, given a patient characteristic, when the patient is the most likely to call back.