IT ALL STARTED WITH A SIMPLE REQUEST

Jim Grayson, PhD, Professor

Cole Phillips

David Newton

Anna Ramanathan

Patrick Hatch

Augusta University

Georgia’s second-oldest and second-largest city, Augusta, is situated on the southern banks of the storied Savannah River.

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Our goal for this presentation

Describe our analytics process for a successful project and how our use of JMP greatly enhanced our ability to meet the needs of our clients

A tale of two models

The first model we thought the customer wanted
and the second model the customer actually needed

It all started at a meeting to update our college strategic plan …

One of our committee members turned to me and said, "Do you have any students that might be able to help me with an analytics problem?"

Maybe??

Can you give me more detail on what you want to do?

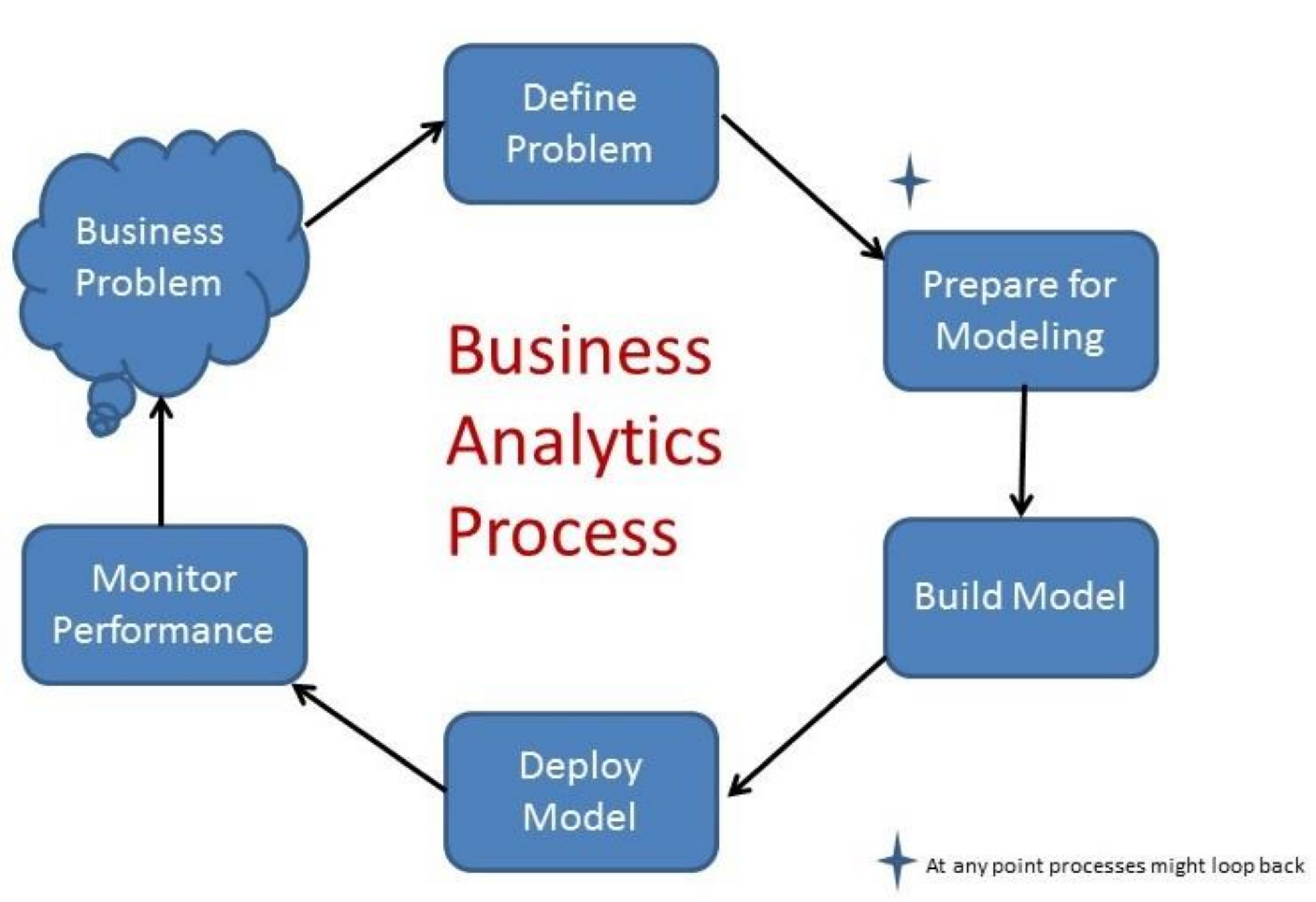
We want to improve the no show rate in our medical clinic

Our current no show is 16.6%

Our goal is to reduce the no show to 12%

Can you help?

Analytics Process



Data

2 Years of patient data

79,000 encounters

Appointment time

Appointment length

Age

Appointment date

Insurance type

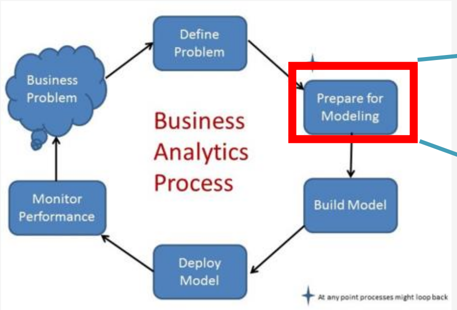
Provider type

Sex

Visit type

Zip code

…



Prepare for Modeling

Define/Acquire Data
- Compile
- Combine
- Structure

Understand Data
- Explore
- Examine
- Characterize

Assess Data Quality
- Missing
- Outliers
- Potential Issues

Restructuring Data
- Recode
- Transform
- Features

Dimension Reduction
- Predictor Screening
- Graphical Exploration for Insights

Appt Date	Appt Date2	Seconds past midnight	Slot Length	Stat 2	Insurance Type 2	Insurance Type 3	Appt Time 2	Appt Time
02/04/2016	Thu	51300	15	N	MEDICARE / Medicaid	MEDICARE	Afternoon	2:15 PM
02/04/2016	Thu	51300	15	N	Other Unknown Champus Selfpay	SELF PAY	Afternoon	2:15 PM
02/04/2016	Thu	52200	15	N	BLUE SHIELD &	BLUE SHIELD &	Afternoon	2:30 PM
02/04/2016	Thu	50400	30	A	Other Unknown Champus Selfpay	SELF PAY	Afternoon	2:00 PM
02/04/2016	Thu	50400	15	A	BLUE SHIELD &	BLUE SHIELD &	Afternoon	2:00 PM
02/04/2016	Thu	49500	30	A	COMMERCIAL &	COMMERCIAL&	Afternoon	1:45 PM
02/04/2016	Thu	45900	30	A	MEDICARE / Medicaid	MEDICARE	Afternoon	12:45 PM
02/04/2016	Thu	37800	15	A	MEDICARE / Medicaid	MEDICARE	Morning	10:30 AM
02/04/2016	Thu	36000	15	A	COMMERCIAL &	COMMERCIAL&	Morning	10:00 AM
02/04/2016	Thu	36600	20	A	MEDICARE / Medicaid	MEDICARE	Morning	10:10 AM
02/04/2016	Thu	35400	30	A	MEDICARE / Medicaid	MEDICAID	Morning	9:50 AM
02/04/2016	Thu	31500	15	A	MEDICARE / Medicaid	MEDICAID	Morning	8:45 AM
02/04/2016	Thu	36000	15	A	MEDICARE / Medicaid	MEDICARE	Morning	10:00 AM
02/04/2016	Thu	35100	15	A	MEDICARE / Medicaid	MEDICAID	Morning	9:45 AM
02/04/2016	Thu	37800	15	A	COMMERCIAL &	COMMERCIAL&	Morning	10:30 AM

Provider Type	Sex	Age	Insurance Type	TOV	Zip	Year1 Arrivals	Year1 Noshows	Year2 Arrivals	Year2 Noshows	Tot Yr 1 Arr + Yr 1 No Show	Tot Yr 2 Arr + Yr 2 No ...
F	F	76	MEDICARE	RET	30814	3	3	3	3	6	6
R	F	2	SELF PAY	RET	29841	0	1	0	0	1	0
F	F	65	BLUE SHIELD MANAGED CARE	RET	30815	2	2	0	0	4	0
R	F	37	SELF PAY	PRO	30904	25	0	24	0	25	24
P	M	50	BLUE SHIELD MANAGED CARE	SDV	29841	6	0	2	0	6	2
F	F	27	COMMERCIAL MANAGED CARE	NEW	30901	2	1	0	0	3	0
P	F	60	MEDICARE	MWV	29841	3	0	0	0	3	0
F	M	71	MEDICARE	RET	30907	3	0	0	0	3	0
F	M	69	COMMERCIAL MANAGED CARE	RET	30906	6	0	11	0	6	11
F	F	73	MEDICARE	RET	30906	3	1	0	0	4	0
F	F	41	MEDICAID	SDV	30901	5	1	3	0	6	3

Other possible Predictors

Feature Engineering

- Other possible Predictors
  - Patient Address
  - Transportation Status
  - Seasonality
  - Weather data
  - Diagnosis information

Business Problem

Analytics Goal

Structured Thinking / Data Sources

Modeling

Development

Segmentation

Insights

Intervention

Research Study

Modeling Approach

- Use **Decision Trees** to communicate with our "customers"
- Use **Profiler** to explain the model
- Use **Column Contributions** to explain "drivers"
- Use **Leaf Report** to show relative **response probability** and **response counts**

We were not getting the results we had hoped for

Our first big breakthrough:

<u>Segment</u> the data by <u>type of visit</u>

- Hospital Discharge Visit
- New Patient Visit
- Annual Visit
- Return Visit
- Same Day Visit
- Other

Our second breakthrough was to identify the most influential visit types

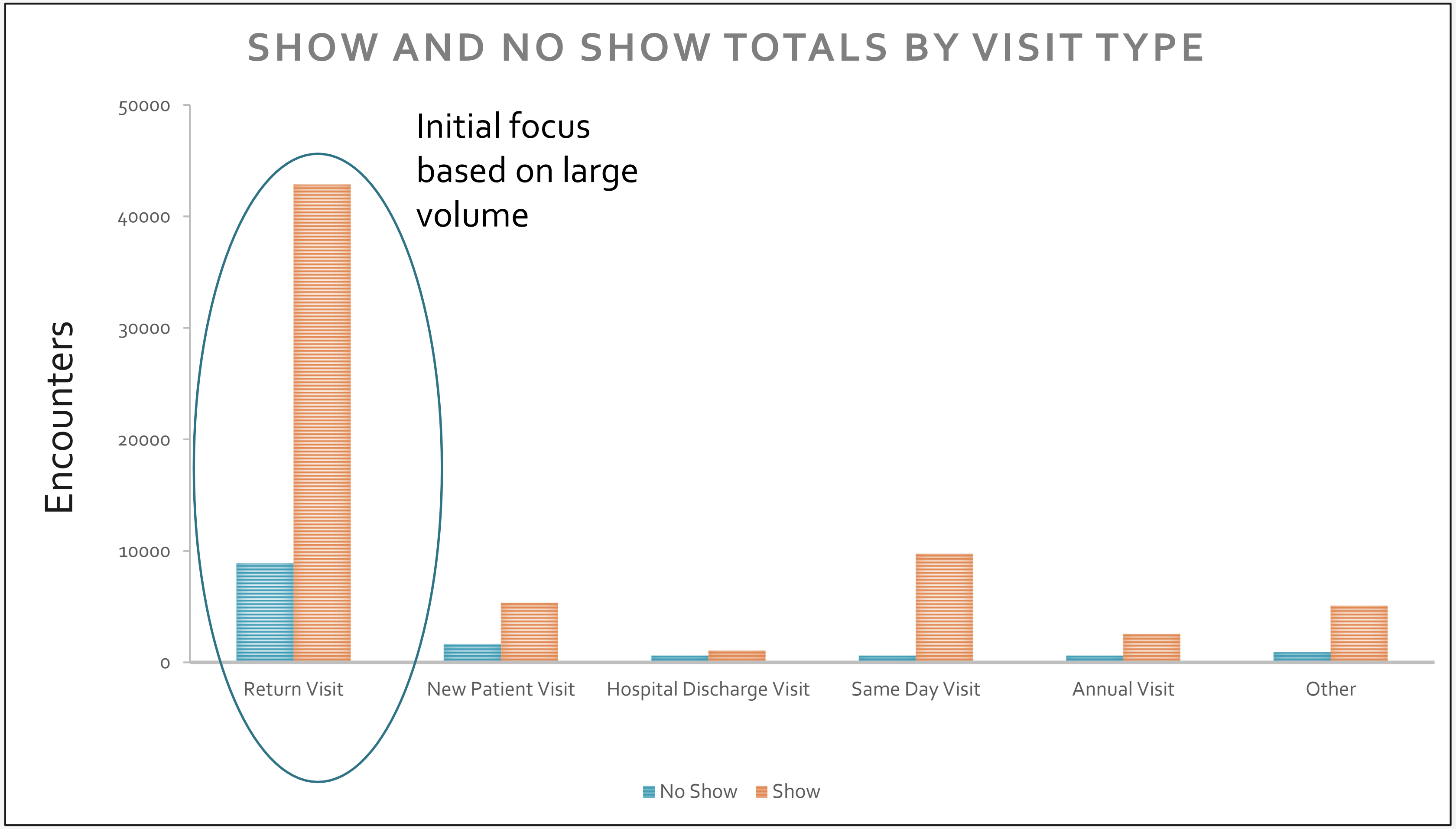
We get "most bang for the buck" with:

- Return Visits
- New Patient Visits
- Hospital Charge Visits

Third breakthrough was to first focus on:

Then there was one

Return Visits



Leaf Report

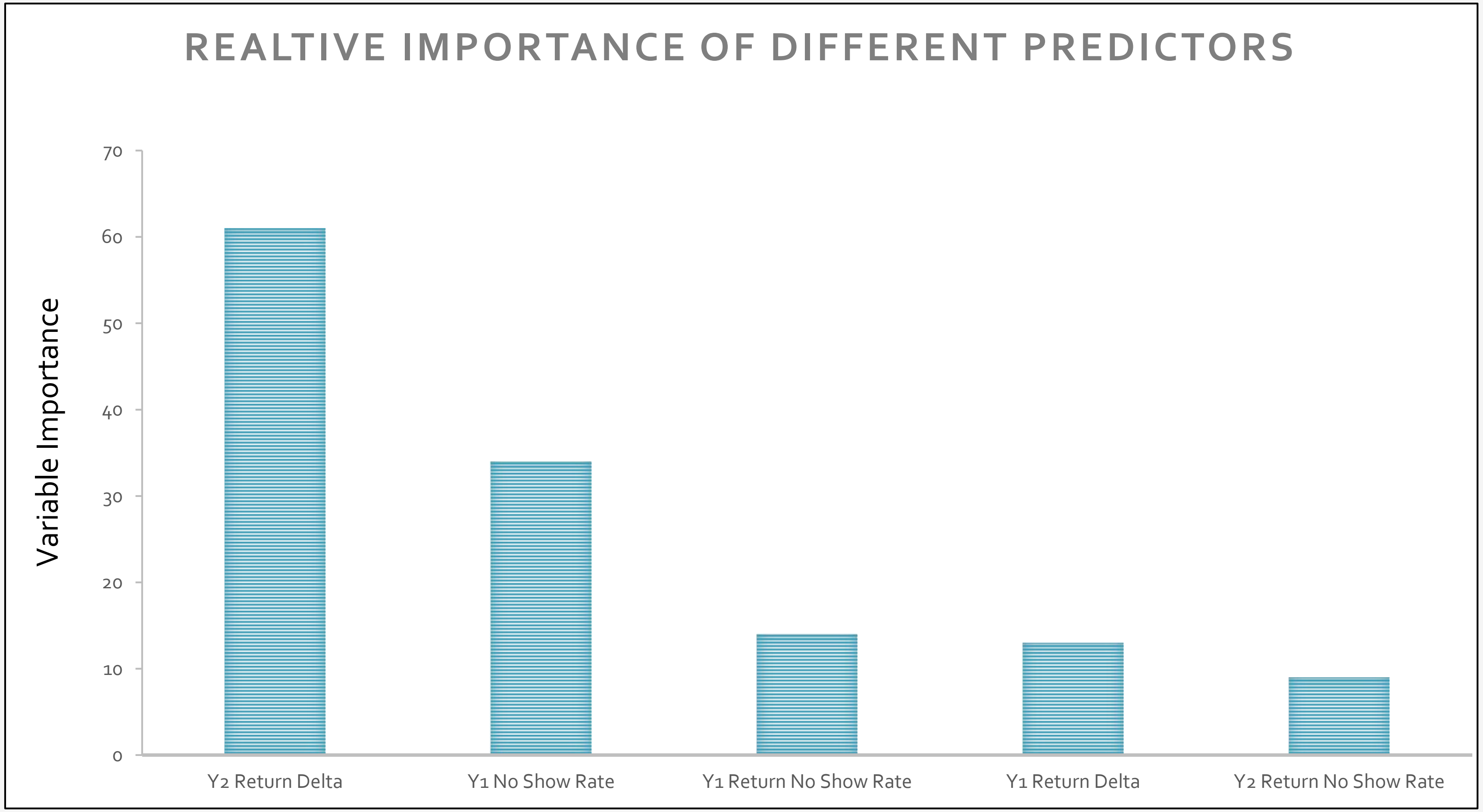
Response Prob

Leaf Label	A	N
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr -...	0.1459	0.8541
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr -...	0.3527	0.6473
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr -...	0.5728	0.4272
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr -...	0.5999	0.4001
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr -...	0.6392	0.3608
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr -...	0.7851	0.2149
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr -...	0.8915	0.1085
Yr 1 Percent No Show<0.1875 not Missing&Yr2 Arr -...	0.6071	0.3929
Yr 1 Percent No Show<0.1875 not Missing&Yr2 Arr -...	0.8619	0.1381
Yr 1 Percent No Show<0.1875 not Missing&Yr2 Arr -...	0.9334	0.0666
Yr 1 Percent No Show<0.1875 not Missing&Yr2 Arr -...	0.9711	0.0289

Response Counts

Leaf Label	A	N
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr ...	127	747
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr ...	424	779
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr ...	469	350
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr ...	1872	1249
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr ...	958	541
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr ...	2134	584
Yr 1 Percent No Show>=0.1875 or Missing&Yr2 Arr ...	2548	310
Yr 1 Percent No Show<0.1875 not Missing&Yr2 Arr ...	446	289
Yr 1 Percent No Show<0.1875 not Missing&Yr2 Arr ...	3370	540
Yr 1 Percent No Show<0.1875 not Missing&Yr2 Arr ...	6122	437
Yr 1 Percent No Show<0.1875 not Missing&Yr2 Arr ...	11190	333

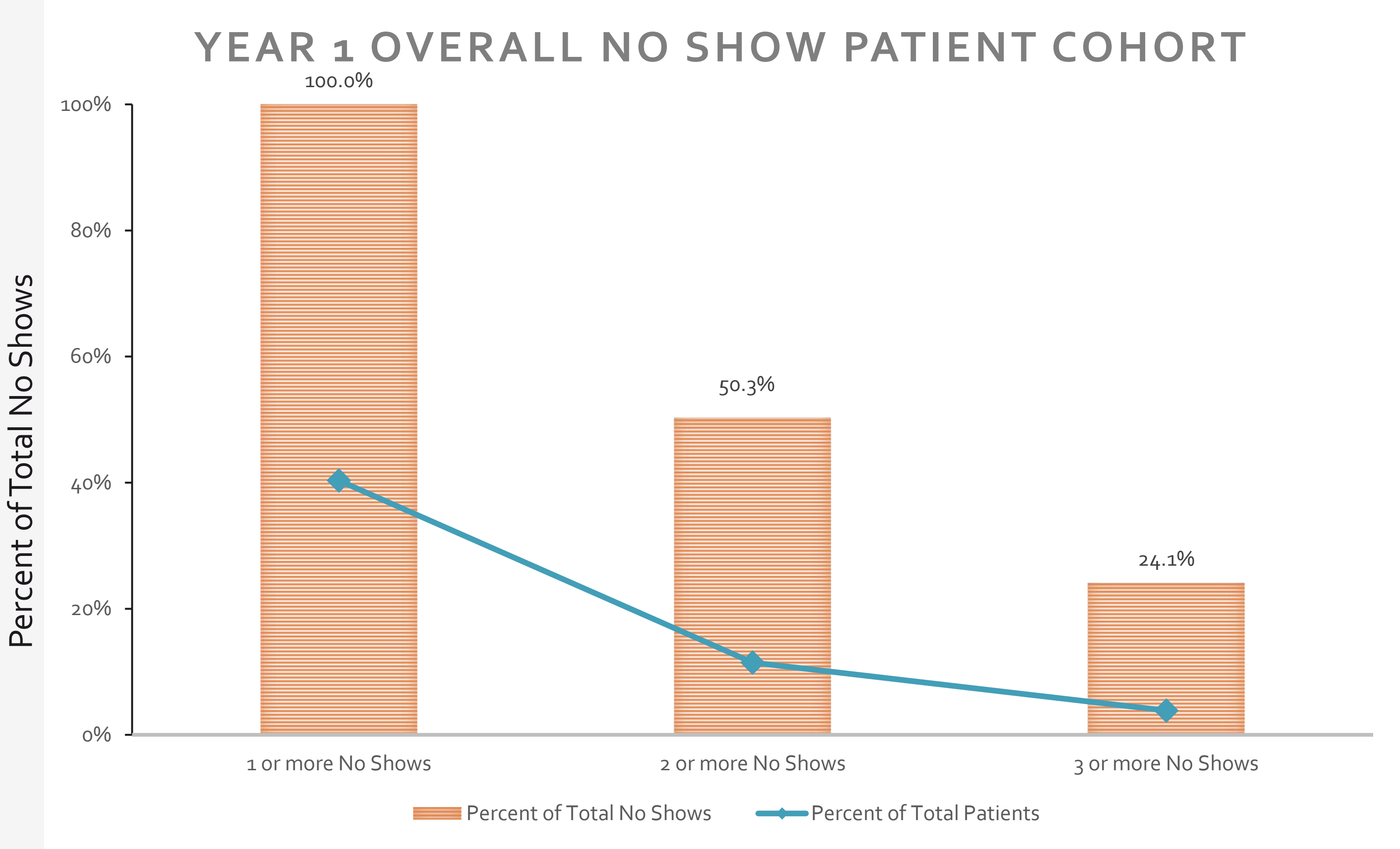
The Fourth Breakthrough was that Past Performance is ***most predictive of No Show***



*No Show Rate: Percentage of visits patient didn't show up to appt.
*No Show Delta: Value of missed appts. in relation to made appts.

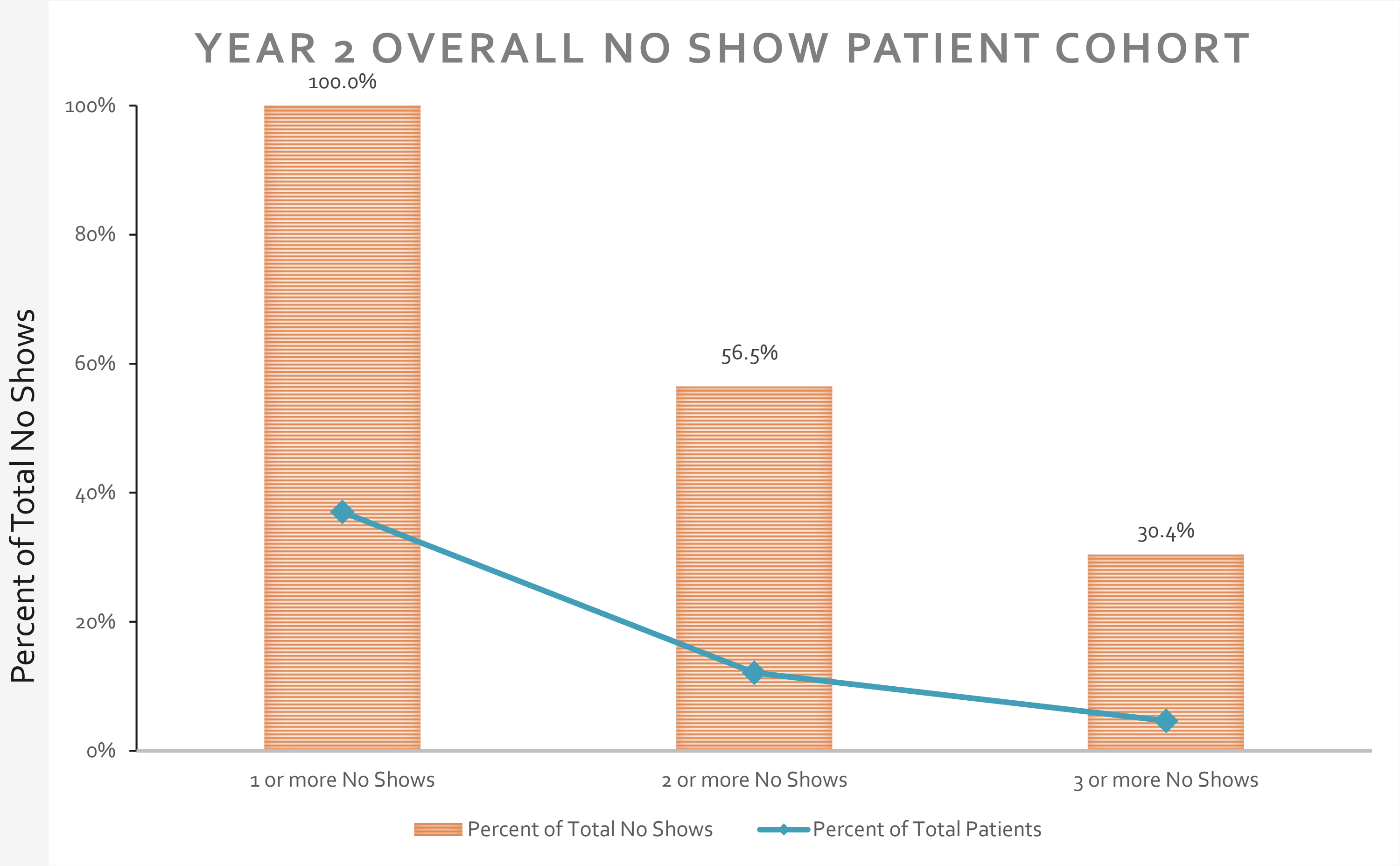
Predictability Meets Practicality

4% of patients account for 24% of No Shows in Y1



Predictability Meets Practicality

5% of patients account for 30% of No Shows in Y2



But don't forget the Health care impact of no shows

- Patients who No Show are at risk of:[1,2]
  - Poorly controlled disease states, especially in diabetes and high blood pressure
  - Not being up to date on preventative services and vaccines
  - Higher quantity of visits to the emergency department and inpatient admissions to the hospital
- Clinic suffers from patient No Shows[3]
  - Lack of continuity of care and disrupted flow
  - Empty slots take up appointment time that could have been used to see another patient

This is where we realized that we had out “goal” all wrong

We really wanted to have patients “show up”.. Not just predict “no shows”

Nudge

Nudge is an application of social norm theory based on behavioral economics.

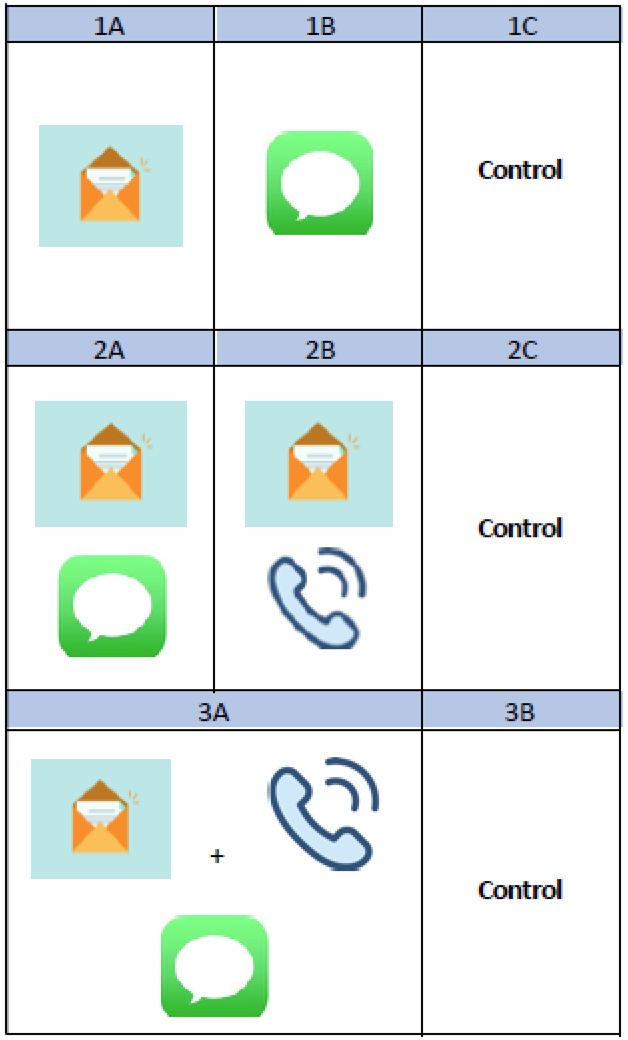
By informing patients that their no-show rate was higher than the overall clinic **we hypothesized that these patients would respond** to improved appointment attendance.

We created a Four Tiered (cohort) intervention aimed at reducing no show rate to 12%

Four Cohorts each randomly split into control and intervention groups

- Cohort 1: n= 116*
  - High Risk Return Visit Patients based on JMP Analysis
- Cohort 2: n= 2,819
  - Patients with 1 No Show in current year
- Cohort 3: n= 843
  - Patients with 2 No Shows in current year
- Cohort 4: n= 527
  - Patients with 3 or more No Shows in current year

Using the knowledge that past performance is most predictive, patients are going to be separated into cohorts based on past no show numbers



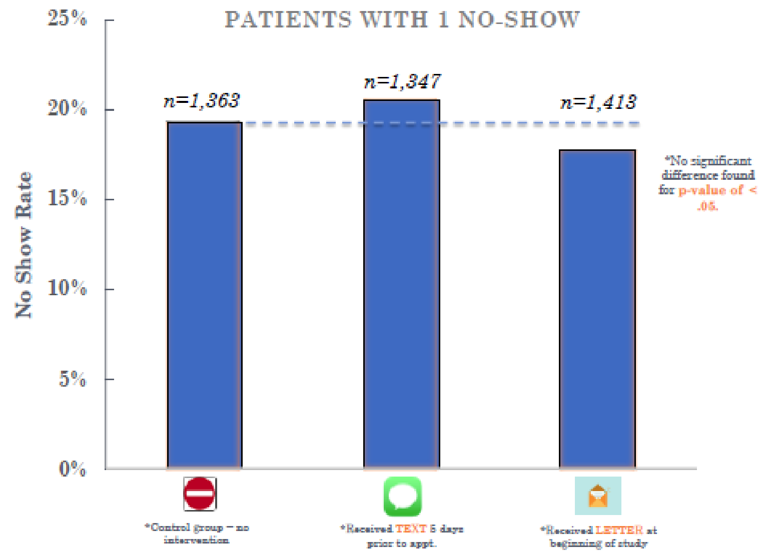
Cohort 1A: (1 missed appointment in previous year)
Received only social norm "behavioral economics" crafted letter at beginning of study.

Cohort 1B: (1 missed appointment in previous year)
Received only social norm "behavioral economics" crafted text message 5 days prior to appointment.

Cohort 2A: (2 missed appointments in previous year)
Received crafted letter at beginning of study + crafted text message 5 days prior to appointment.

Cohort 2B: (2 missed appointments in previous year)
Received crafted letter at beginning of study + personal staff phone call 5 days prior to appointment.

Cohort 3A: (3+ missed appointments in previous year)
Received crafted letter at beginning of study + personal staff phone call 5 days prior to appointment + crafted text message 1 day prior to appointment.



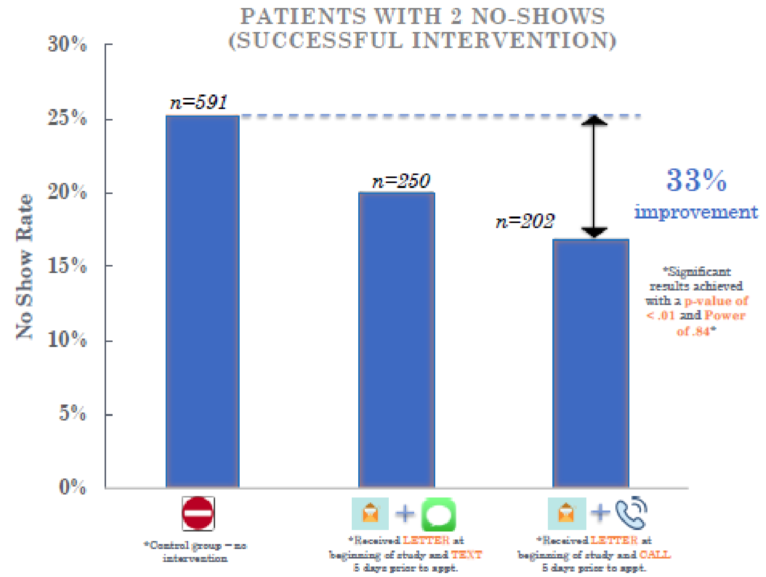
Cohort 1A:
Non-significant decrease of 8.3% in no-show rate.

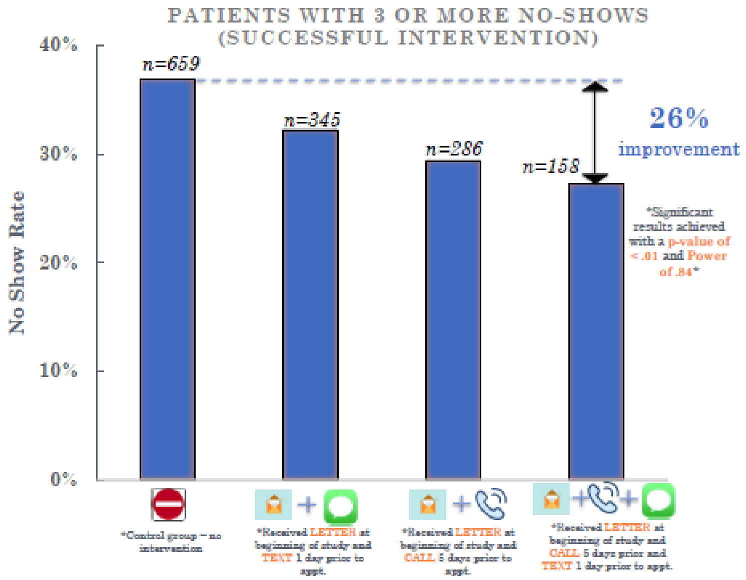
Cohort 1B:
Non-significant increase of 6.5% in no-show rate.

Cohort 2A:
Non-significant decrease of 21% in no-show rate.

Cohort 2B:
Statistically significant decrease of **33%** in no-show rate.

Cohort 3A:
Statistically significant decrease of **26%** in no-show rate.





Future Directions for better no show Prediction

- Possible Interventions:
  - Phone call from staff person proven to be better
  - Text message is cheaper and less invasive
  - Letter
  - Group Meeting
  - Allow re-book of appointments when you call patients
  - Require patients to be active in appointment by calling a week in advance to "confirm" tentative slot
  - Advanced access schedule
  - Increase clinic accessibility
  - UberHealth

Lesson Learned?

Beginning .. Middle .. End

The Middle is the exciting part .. developing the model and seeing predictive improvements

But perhaps the other two pieces are what makes us or breaks us …

Beginning .. understanding what the customer wants … probing to know the true goal which might not be conveyed because the client is thinking “analytics”

End .. Being willing to see the “aha” moment that this is not really “success” for the customer and being willing and able to see that and respond