Department of
Family & Community
Medicine

University of California,
San Francisco

Empanelment and Panel Size Weighting

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ADFM Webinar March 6, 2017

Webinar Objectives

- Review key elements of empanelment
- Focus on weighting of patient panels based on patient complexity/work demand
  - Conceptual framework for patient weighting
  - UCSF weighting model: big data model using Epic EHR data

10 Building Blocks of High Performing Primary Care

UCSF Department of Family & Community Medicine
Center for Excellence in Primary Care

T Bodenheimer et al AnnFamMed March 2014

Empanelment is an Enabler of Other Building Blocks

Essential for alternative PC payment models involving capitation/panel based payment

University of California Primary Care Collaborative

UNIVERSITY OF CALIFORNIA UC Health

Center For Health Quality And Innovation

Calculating Primary Care Panel Size

January 2017

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http://www.ucop.edu/uc-health/_files/uch-chqi-white-paper-panel-size.pdf

The 4 Elements of the Empanelment Process

- Attributing patients to a PCP and PC practice
- Establishing the target “right size” panel for a PCP clinicalFTE
- Weighting each PCP’s panel to adjust for variation in patient complexity/PCP work demand
- Managing panel sizes to the “right size” target

Traditional Approach to Weighting of Patients: "Risk Adjusting" for Patient Characteristics

- Demographics
  - age, gender
  - SES (e.g., insurance type; census derived geocoded "deprivation" indices)
- Diagnostic codes
  - Usually from billing data
- Examples
  - HCC (Medicare Advantage)
  - DXG (private insurers)
  - Johns Hopkins Ambulatory Care Groups

Example of an Age-Gender Weighting Scheme From Tantau & Associates

Age and Gender Specific Panel Adjustments				
Age Range	Age (Mos)	Rel. Wt.	Male	Female
0	0	11	5.02	4.66
1	12	23	3.28	2.99
2	24	35	2.05	1.97
3	36	47	1.72	1.62
4	48	59	1.47	1.46
5-9	60	119	0.98	1.00
10-14	120	179	0.74	0.79
15-19	180	239	0.54	0.72
20-24	240	299	0.47	0.70
25-29	300	359	0.60	0.82
30-34	360	419	0.63	0.84
35-39	420	479	0.66	0.86
40-44	480	539	0.69	0.89
45-49	540	599	0.76	0.98
50-54	600	659	0.87	1.10
55-59	660	719	1.00	1.20
60-64	720	779	1.17	1.31
65-69	780	839	1.36	1.46
70-74	840	899	1.55	1.60
75-79	900	959	1.68	1.70
80-84	960	1019	1.70	1.66
85+	1020	9999	1.57	1.39
			1.57	1.39

Drawbacks & Limitations of Traditional Methods

- Do not directly measure primary care work effort
- Poor predictive power for primary care visits/work
- Often proprietary “black boxes”
- “Gaming” of diagnostic coding

Alternative Approach: Directly Measure the Primary Care Work Effort Using Patient-Level Utilization Data

Mark Murray Visit Based Method for Comparing Supply and Demand

B	C	D	Solve for
↓	↓	↓	↓
Days in Clinic per year **X**	Visits per day (productivity) **=**	Average patient visits per year **X**	Panel Size

Total visits available in a year — *Total visits patients create*

Supply = Demand

The Drawback of a Purely PCP-Visit-Based Weighting Method

- Growing amount of PCP patient care work activity occurs outside of in-person patient visits
  - Patient portal messaging, phone calls
  - Care coordination
  - Other

UCSD Primary Care Changes in Non Visit Workloads

UCSD Primary Care Ratio of Non Visit Encounters to Visits						
	FY 12	FY13	FY14	FY15	FY16	% Change FY16:FY12
Ratio of Non-Visit Visits Per In-Person Visit	2.30	2.41	2.44	2.59	3.01	31%
MyChart Touches	0.38	0.45	0.55	0.64	0.88	132%
Nurse Touches	0.05	0.05	0.04	0.04	0.04	-29%
Refill Touches	0.70	0.65	0.65	0.69	0.76	8%
Telephone Touches	1.13	1.23	1.18	1.19	1.31	16%

Slide from Tyson Ikeda, MD

UC San Diego Health

UCSF Panel Weighting Model Approach

- Take advantage of the EHR (Epic) for a "big data," machine learning computational approach
- Use a huge amount and diversity of utilization data to identify clusters of patients based on patterns of utilization
- Eschew diagnosis codes
- Involve front line PCPs in iteration of model

JMIR Publications
The Leading eHealth Publisher
JMIR Medical Informatics

Original Paper

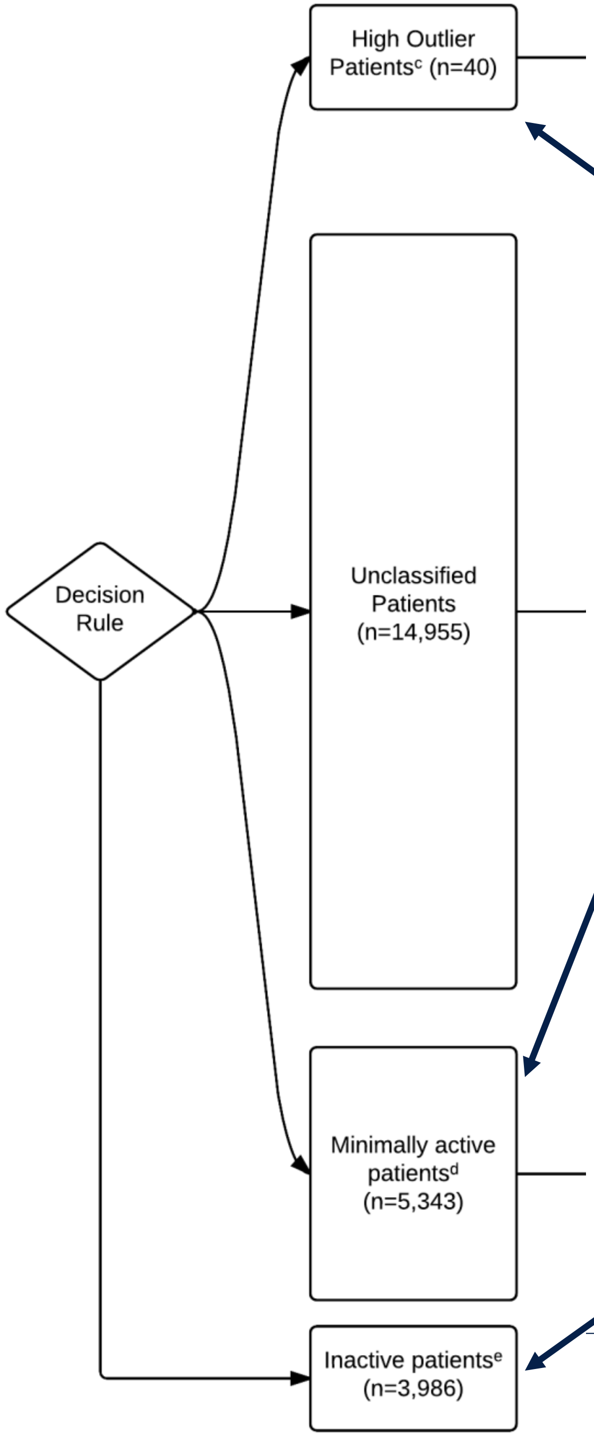
Weighting Primary Care Patient Panel Size: A Novel Electronic Health Record-Derived Measure Using Machine Learning

Alvin Rajkomar[1*], MD; Joanne Wing Lan Yim[2*], PhD; Kevin Grumbach[3,4], MD; Ami Parekh[1,3], MD, JD

JMIR Med Inform 2016;4(4):e29) doi:10.2196/medinform.6530

UCSF Rajkomar Methodology

- Patient Sample:
  - 35,000 adults continuously empaneled in UCSF Health Primary Care practices Feb 2013-Jan 2015; 70% (N=24,000) used for model development, 30% for validation
- Data from year 1 included in model:
  - PC visits, specialty visits, ED visits, UC visits, hospitalizations, missed appointments, infusion center visits, radiology visits, telephone encounters, MyChart messages, number of medications
- Use decision rules and "k-cluster mean" analysis to create clusters of patients representing different levels of intensity of primary care work
- Assign weights to each final cluster



Step 1: Decision Rule Clustering

High outlier patients were defined to have greater than 6 standard deviations above the mean of number of primary care visits

Minimally active patients were defined to meet all the following criteria:
≤1 primary care visit per year,
0 ED visits,
0 hospitalizations,
≤4 specialty visits per year,
≤2 telephone encounters per year,
≤6 electronic messages to the patient per year.

Inactive Patients were defined to have no encounters in time period

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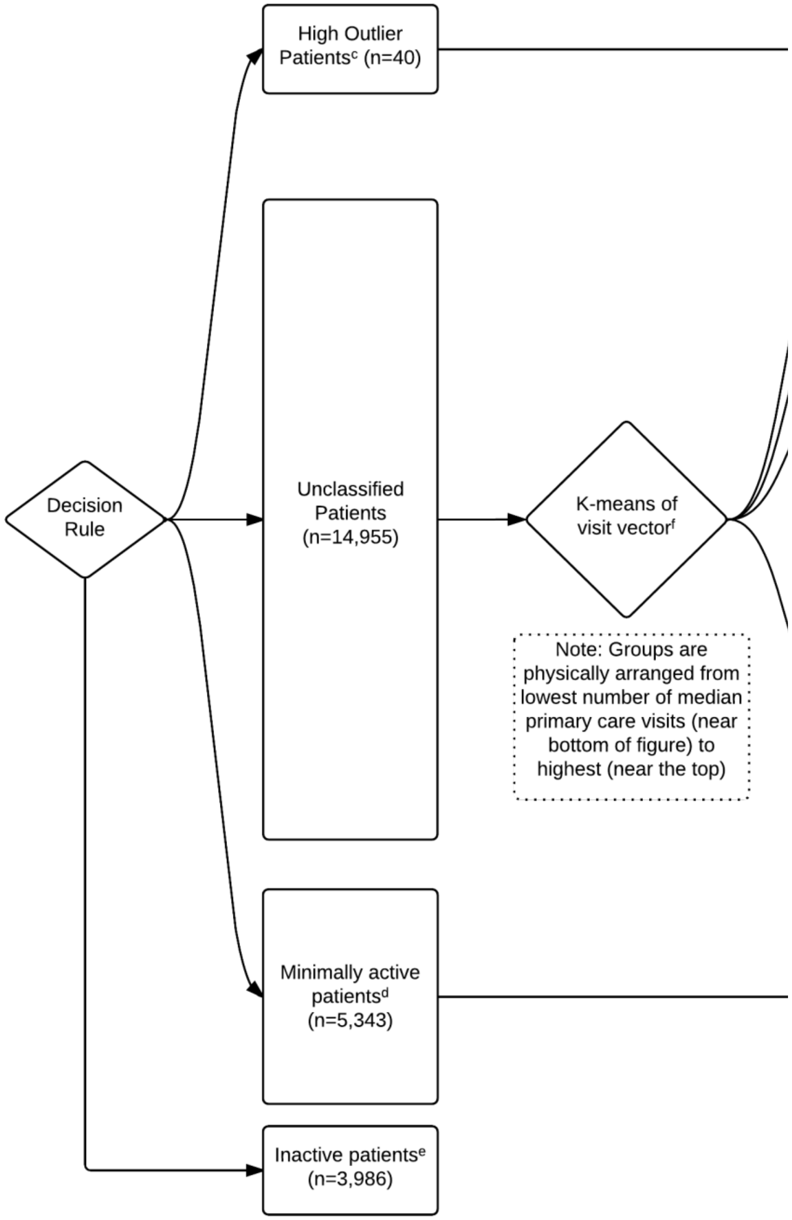

Step 2: Use K Means Analysis to Identify Utilization Clusters for Patients Unclassified by Step 1

A visit vector was created for each patient, with each component representing the sum of visits of each encounter type we analyzed.

Components of visit vector:

Weighted PCP visits by number of medications
No shows to PCP
Telephone encounters to PCP
Medical and Surgical Subspecialty visits
Urgent Care
ED visits
Emergent Hospitalizations
Routine Hospitalizations
Infusion and Transfusion Center visits
Radiology or Procedures
(note: Electronic Messaging is not in this vector)

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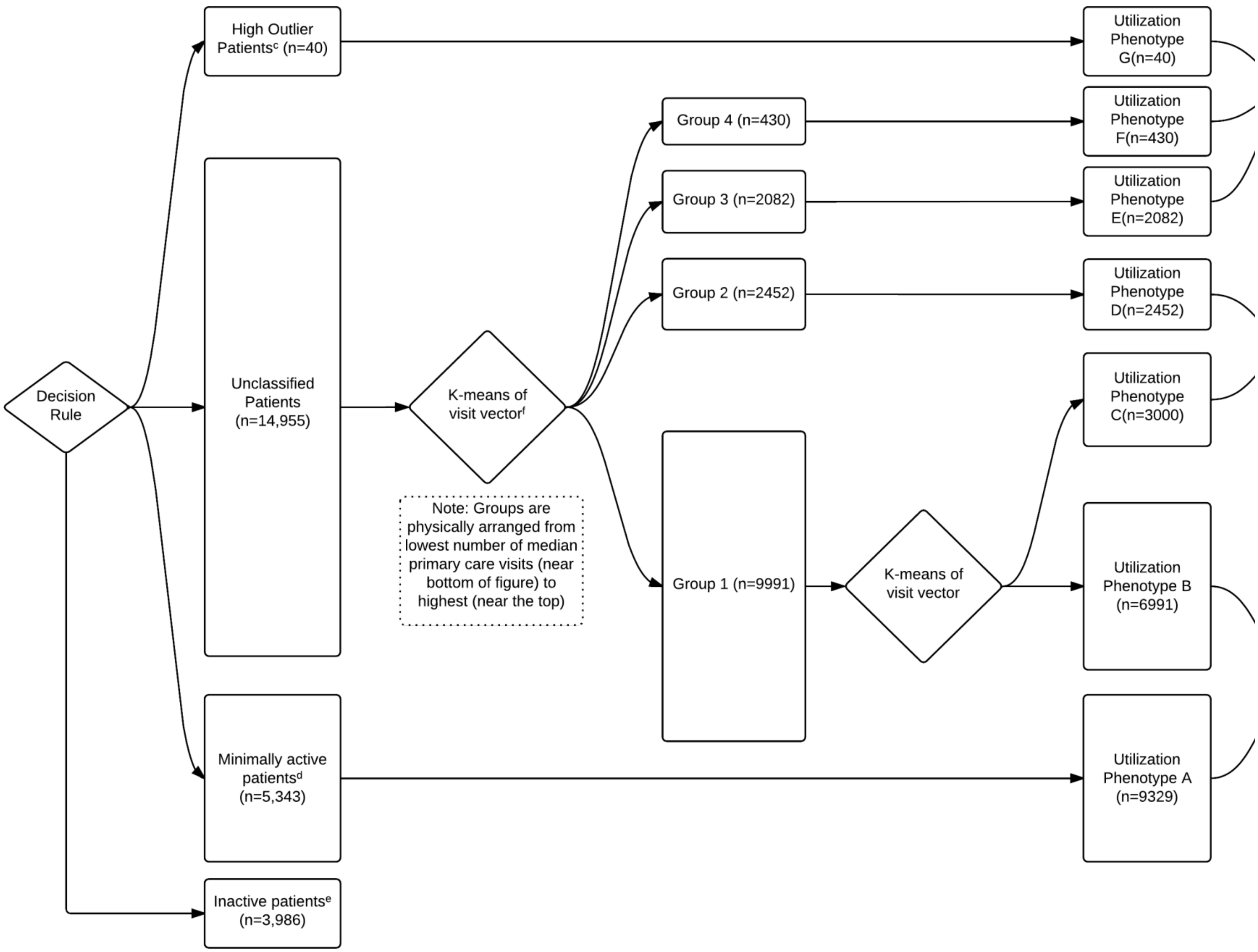
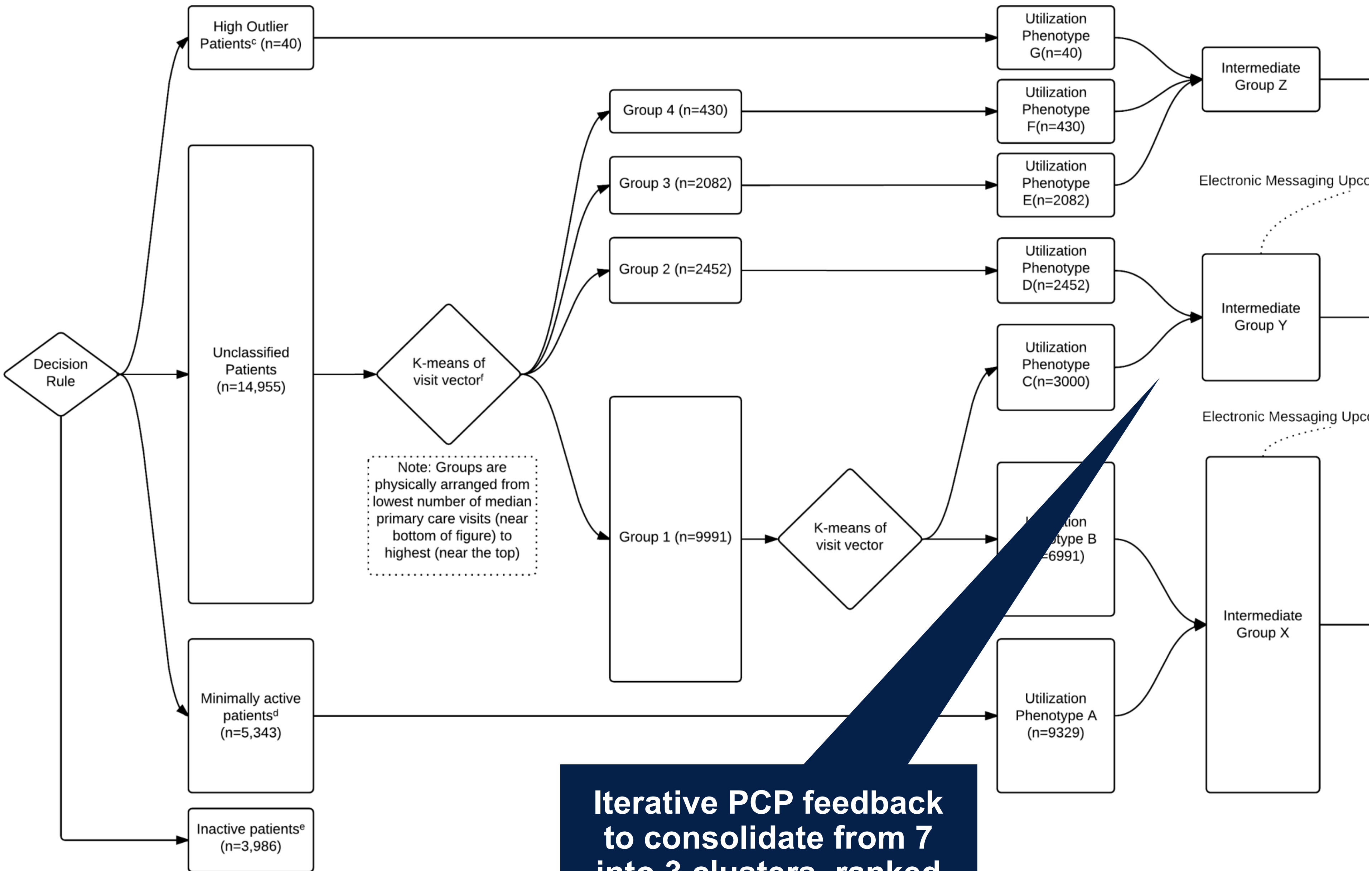

High Outlier Patients[c] (n=40)
Utilization Phenotype G(n=40)
Group 4 (n=430)
Utilization Phenotype F(n=430)
Group 3 (n=2082)
Utilization Phenotype E(n=2082)
Group 2 (n=2452)
Utilization Phenotype D(n=2452)
Decision Rule
Unclassified Patients (n=14,955)
K-means of visit vector[f]
Utilization Phenotype C(n=3000)
Note: Groups are physically arranged from lowest number of median primary care visits (near bottom of figure) to highest (near the top)
Group 1 (n=9991)
K-means of visit vector
Utilization Phenotype B (n=6991)
Minimally active patients[d] (n=5,343)
Utilization Phenotype A (n=9329)
Inactive patients[e] (n=3,986)



Iterative PCP feedback to consolidate from 7 into 3 clusters, ranked by annual # PCP visits

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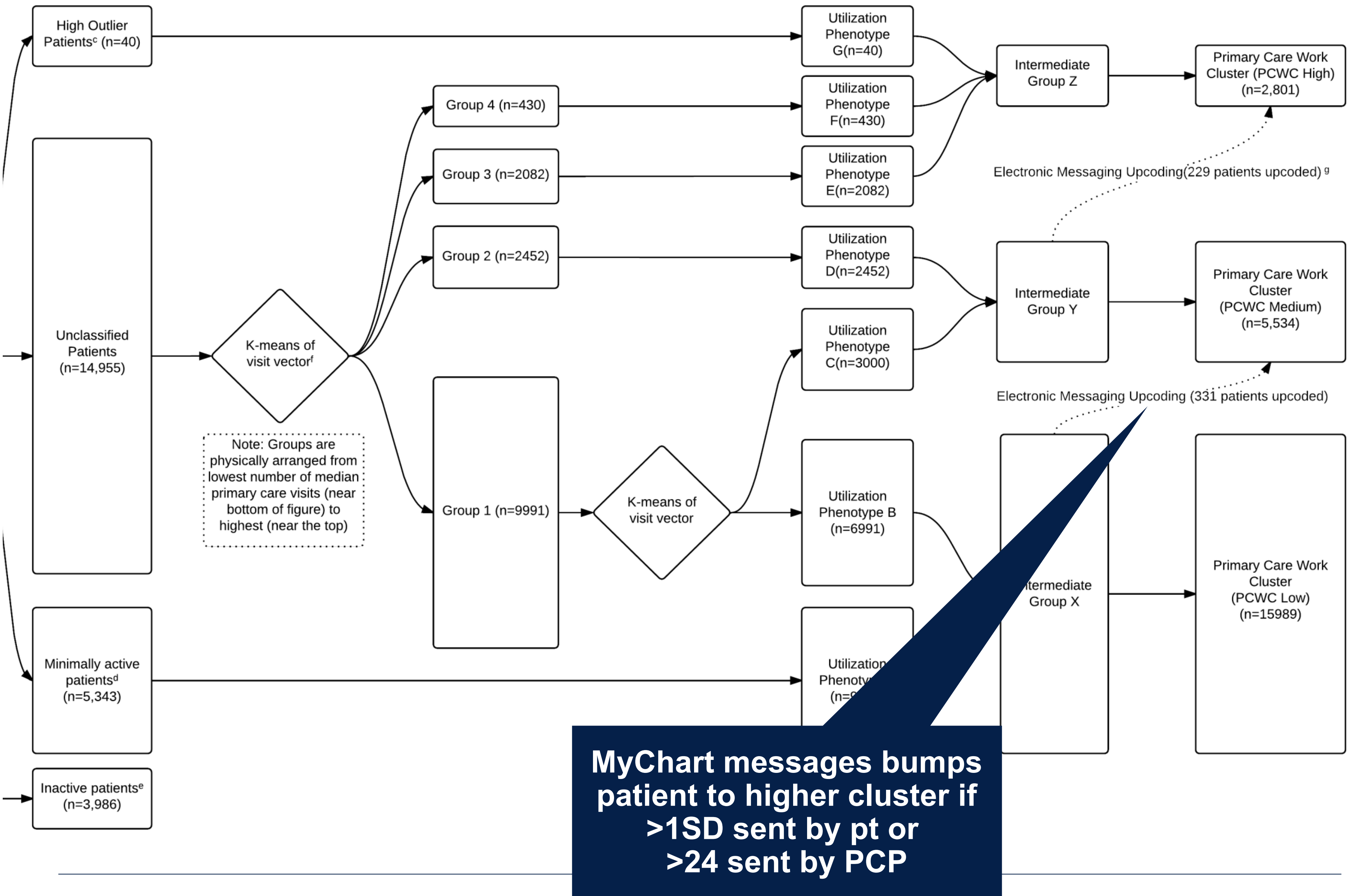

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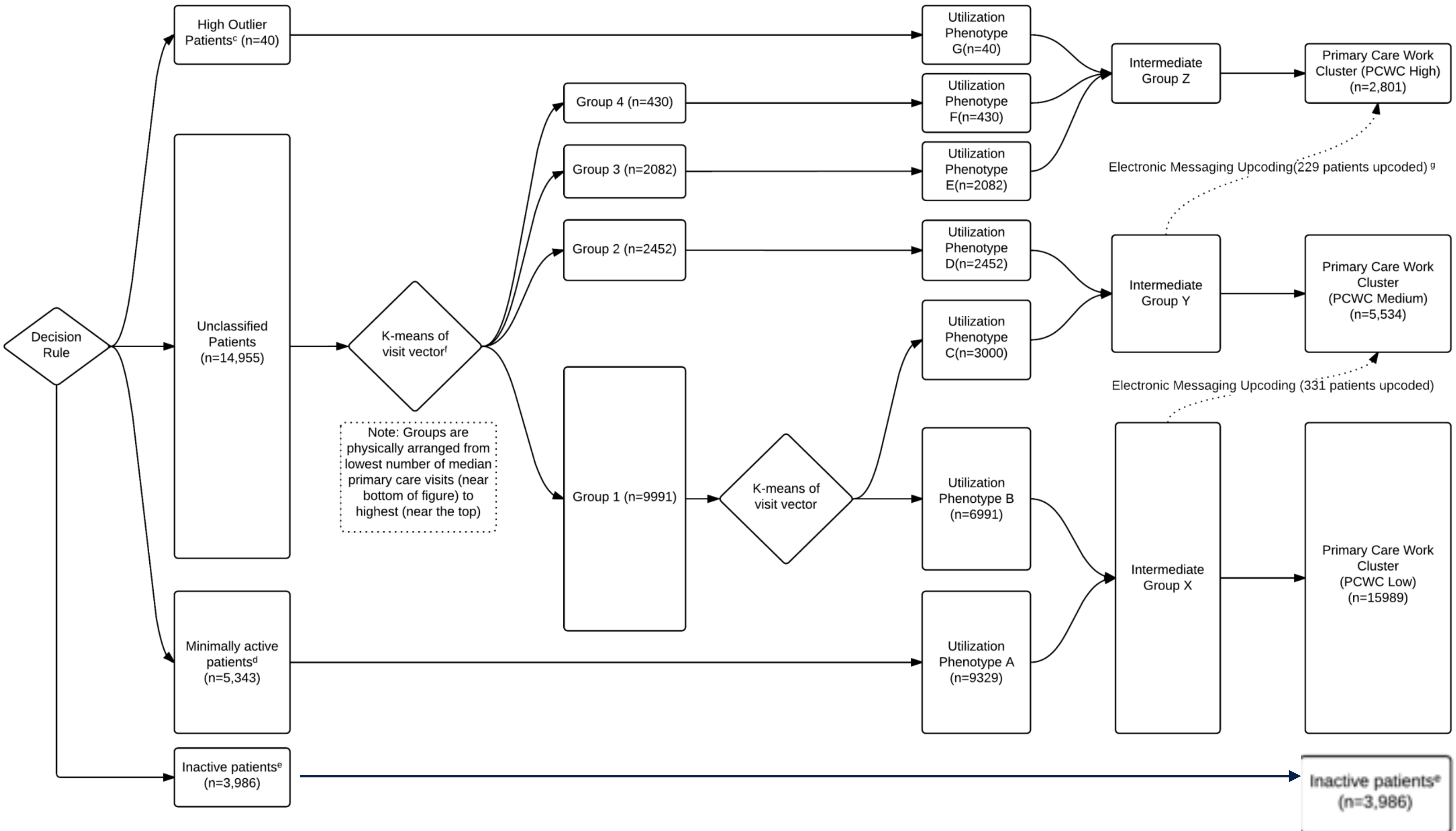
Utilization Phenotype C(n=3000)
Utilization Phenotype B (n=6991)
Intermediate Group Z
Intermediate Group Y
Group X
Primary Care Work Cluster (PCWC High) (n=2,801)
Primary Care Work Cluster (PCWC Medium) (n=5,534)
Primary Care Work Cluster (PCWC Low) (n=15989)
Electronic Messaging Upcoding(229 patients upcoded) [g]
Electronic Messaging Upcoding (331 patients upcoded)
MyChart messages bumps patient to higher cluster if >1SD sent by pt or >24 sent by PCP

Final Set of 4 PC Work Clusters



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Validating Clusters: Predicting Yr 2 PCP Visits in Validation Sample

Linear model of primary care telephone encounters and office visits based on demographic variables and baseline utilization phenotype

Model Predictors	Adjusted R^2	AIC[a]
Age-Sex	0.166	60780
Payor	0.128	61495
Year 1 visit count	0.259	57724
Rajkomar Clusters	0.330	55088
Age-Sex and Payor	0.209	59450
Age-Sex, Payor, and Yr 1 visits	0.343	54813
Age-Sex Payor, and Rajkomar Clusters	**0.394**	**52769**

[a]Akaike Information Criterion goodness of fit

Final Step

- Assign weights to each cluster
  - Based on ratio of median annual PCP visits for patients in high and medium clusters relative to low cluster
  - Inactive cluster assigned weight of 0.05
  - Then standardize so that Σweighted= Σunweighted

Final Weights

Requirements:
Total Effective Patient Population equals Actual Population Size

$$N_{total\ population} = \sum_{i \in \{,l,m,h\}} (w \cdot X_i \cdot N_i) + 0.05 \cdot N_{inactive}$$

$$w = \frac{N_{total\ population} - 0.05 \cdot N_{inactive}}{\sum_{i \in \{l,m,h\}} X_i N_i}$$

$N_i \stackrel{\text{def}}{=} number\ of\ patients\ in\ cluster\ i$

$X_l = median\ number\ of\ PCP\ visits\ of\ cluster\ low$

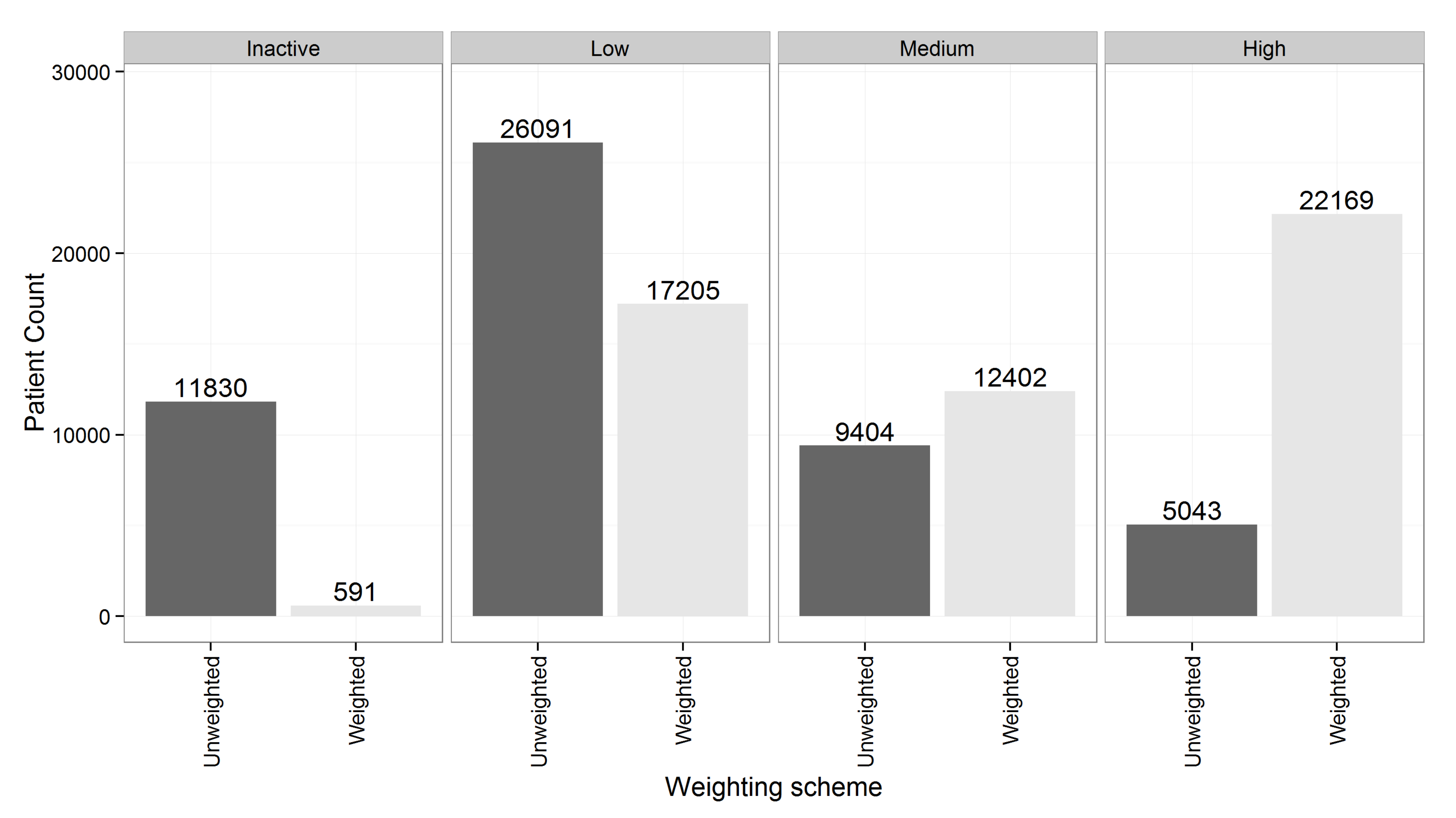
$$X_m = \frac{median\ number\ of\ PCP\ visits\ of\ cluster\ medium}{X_l}$$

$$X_h = \frac{median\ number\ of\ PCP\ visits\ of\ cluster\ high}{X_l}$$

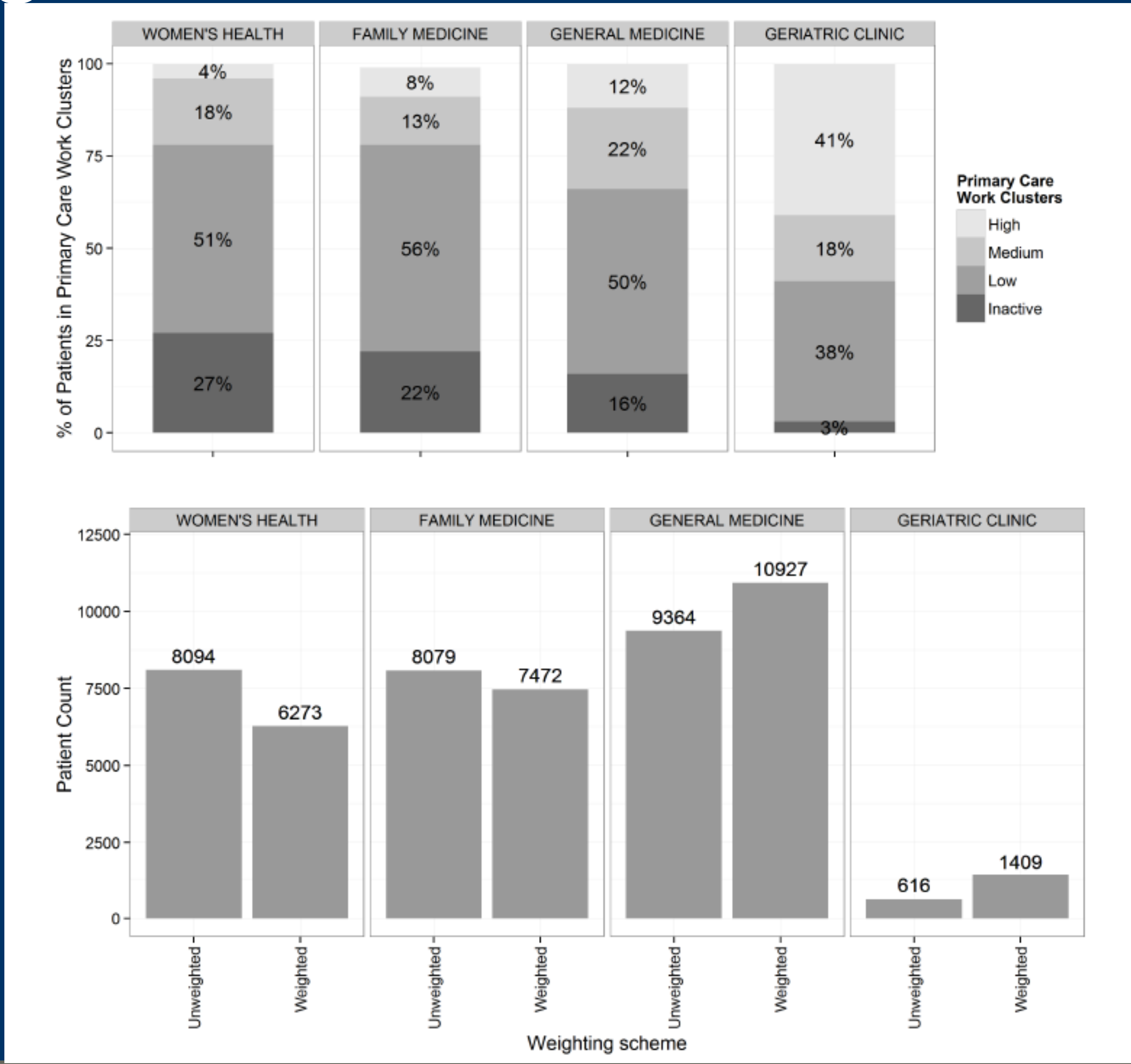
Weight for each group is: w ·(X_i)

Cluster	Weight
Inactive	0.05
Low	0.659
Medium	1.319
High	4.396

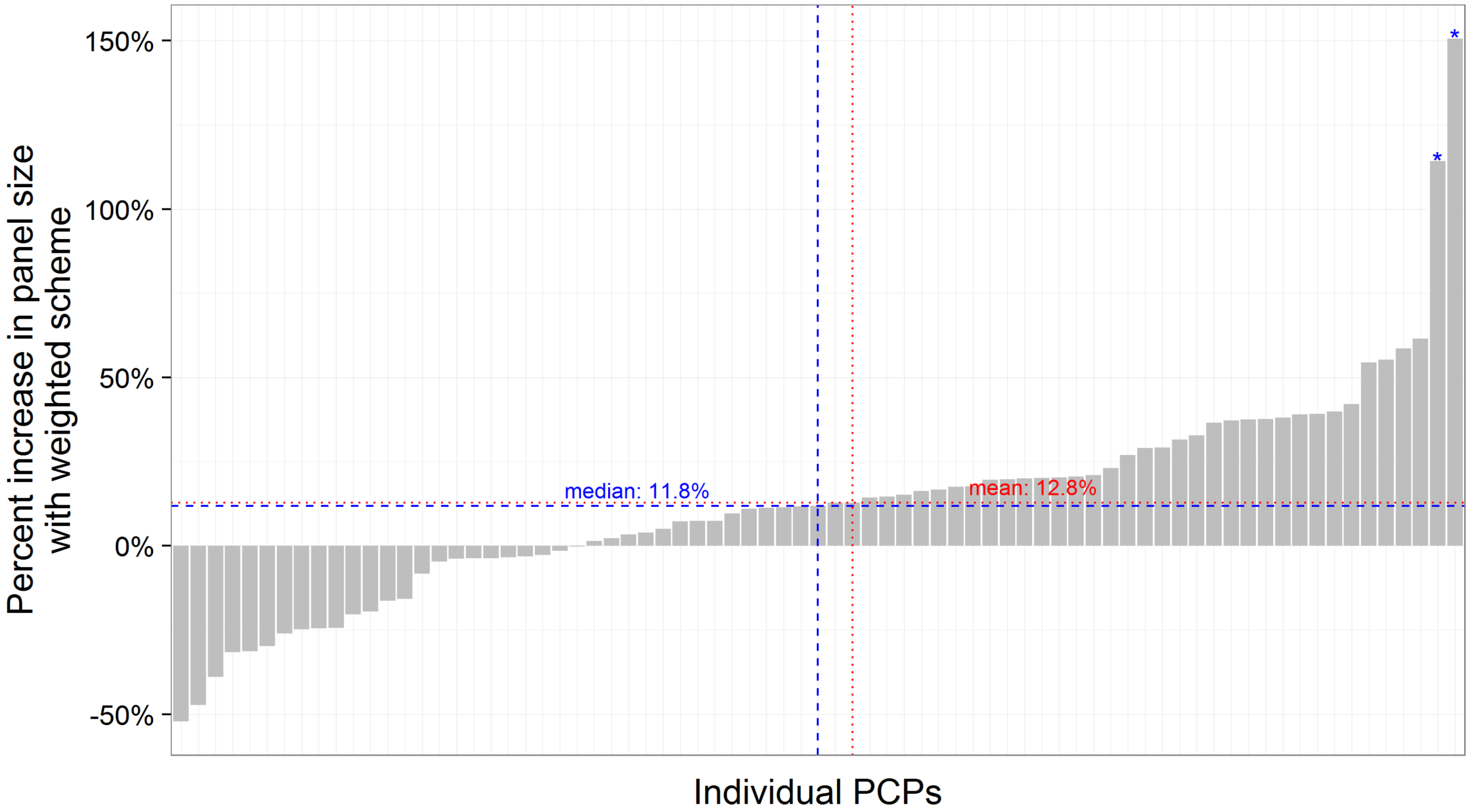
Unweighted and Weighted Patient Counts, By Cluster



Weighted Panels at the Clinic Level



Relative Change in Panel Size for Each PCP After Weighting



Operationalizing at UCSF Health

- Involving PCPs in method development important!
- Running algorithm quarterly to update assignment of all empaneled PC patients to 1 of the 4 clusters
- Output to Clarity to create dashboards every month with unweighted and weighted panel sizes for every PCP and clinic
- Using weighted panel size for judging each PCP's and clinic's panel relative to target right size panel, informing decisions to open and close panels to new patients
- Will next be factored into funds flow panel-based payments to departments

Limitations

- Supplier-induced demand and inefficient practice style can result in higher weights
  - No judgment about appropriateness of utilization
  - Every method can be gamed
- Lag in new patient utilization contributing to weights
- Adults only
  - Similar model could be developed for children
- Normalized within a single system
  - Cannot be used to compare complexity of patients across systems, unless they all use the same algorithm and standardize to collective N

Questions and Comments

For those interested in more details on programming the algorithm and creating output:

- Not feasible for our UCSF team to provide TA to individual health systems
- Much of the programming specifications are contained in our article
- Could arrange a follow up webinar with our UCSF analyst if a group of ADFM members and their tech teams desire a session on technical specifications