Real-time stats for real-time problems

The development of a risk tool to predict and prevent psychiatric crises in Multnomah County, Oregon

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Background

- Multnomah County--most of Portland, a few of the suburbs
- Mental Health & Addiction Services Division (MHASD)
  - Direct services
  - 24/7 crisis line
  - Care coordination and outreach
  - Management of Medicaid behavioral health benefit for county Medicaid members (Oregon is an ACA expansion state)
    - Not just authorizing treatment and paying claims--partnering with community providers and CCO to improve care, improve access, further behavioral/physical healthcare integration, increase system capacity, monitor outcomes, etc.; invested in the health of the system as a whole

Background

- Acute care--inpatient psychiatric hospitalizations, behavioral health-driven ER visits, psychiatric emergency services
  - Want to reduce acute care utilization by engaging clients in different levels of care that sustainably address their needs
- We follow up on hospitalizations and ED visits...but what if we could get there *before* they happened?
- Predictive risk modeling*
  - Uses standard statistical analyses of past events to help predict future ones reliably

**Many thanks to the Oregon Criminal Justice Commission for giving us the "behind the scenes" details of their predictive risk tool; many of our methodology decisions were informed by their work.*

Preparation & process

- Our events:
  - Acute care event
    - Inpatient psychiatric hospitalizations
    - Psychiatric emergency services (PES)
    - Emergency department visits attributable to mental health and/or substance use diagnoses
- Our sample:
  - HSO members with 1+ year coverage & SPMI
- Our time period:
  - January 1, 2015 to June 30, 2017 (2.5 years)

Result: 13,158 clients; 11,222 acute care events

Preparation & process

- Our data sources:
  - Healthcare claims
  - Call center records
  - Medicaid enrollment data
- Variables to explore:
  - Met with front-line mental health staff for input on what they perceived as contributing factors and/or indicators* of impending crisis, common traits of high utilizers, etc.

**An indicator doesn't have to cause the event, but can be a warning sign; e.g., multiple calls to the crisis line before a hospitalization*

Analysis

- Multiple-failure Cox survival analysis (Stata's stcox)
  - Better suited to data structure
    - Didn't want to lose data on multiple events by one person; accounts for different lengths of observation time, acknowledges that acute care event can happen after observation period ends
- Logistic regression (Stata's logit, vce(cluster id), and lroc)
  - More easily interpreted in terms of predictive fit (use of area under ROC curve); more familiar; can still adjust for multiple events by individuals
- Comparing the models
  - Output/models very similar
  - Decided to use logistic to proceed

Analysis

- Significant non-demographic variables (odds ratio):
  - No recent mental health outpatient history (4.5)
  - Multiple SPMI-level diagnoses (4.3)
  - History of substance use (2.9)
  - Week with 2+ crisis line calls (2.9)
  - History of homelessness/housing instability (1.7)
  - Receiving SSI for disability (1.7)
  - Healthcare encounters with respiratory (1.6) or pain issues (1.5) as primary diagnosis
- Area under the ROC curve: 0.85
  - 0.9 to 1 considered excellent; 0.8 to 0.89 → very good

Validating results

- #1: Equity
    - Avoid systematically under/over-predicting for any population
        - Ran model *without* demographics included, on each individual race, age, sex, language, as well as random combinations
            - Intent: ensure it works well for different populations
                - **Short answer: yes, it does!**
- #2: Different, but similar, sample
    - Run the exact same models with all SPMI members with under 1 year of coverage (pop. of 3,380)
        - ORs virtually the same, ROC of 0.84; important because we often work with incomplete data → realistic scenario
            - Good sign to proceed!

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```
. logit eventhappened multipledx_binary substanceuse english race1_black race2_asian race3_white
> race4_hispanic race5_native race6_pacisl male ssi homeless_or_supported weekwithatleast2calls p
> ain respiratory no_op_atall age_18to29 age_30to39 age_40to49 age_50to59 age_60to69, vce(cluster
>  policyid) or

Iteration 0:   log pseudolikelihood = -16829.735
Iteration 1:   log pseudolikelihood = -11712.316
Iteration 2:   log pseudolikelihood = -11696.867
Iteration 3:   log pseudolikelihood = -11696.848
Iteration 4:   log pseudolikelihood = -11696.848

Logistic regression                             Number of obs     =     24,390
                                                Wald chi2(21)     =    3992.81
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -11696.848               Pseudo R2         =     0.3050

                                  (Std. Err. adjusted for 13,158 clusters in policyid)
```

eventhappened	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
multipledx_binary	4.334528	.2203021	28.86	0.000	3.923553	4.78855
substanceuse	2.928598	.157988	19.92	0.000	2.634755	3.255211
english	1.11377	.0993887	1.21	0.227	.9350551	1.326641
race1_black	.8849463	.058804	-1.84	0.066	.7768824	1.008042
race2_asian	.7792272	.1073113	-1.81	0.070	.5948957	1.020675
race3_white	1.061181	.0225586	2.79	0.005	1.017875	1.106329
race4_hispanic	.8468447	.0945183	-1.49	0.136	.6804547	1.053922
race5_native	.9595662	.1646808	-0.24	0.810	.685475	1.343254
race6_pacisl	.8662499	.2765293	-0.45	0.653	.4633591	1.619454
male	1.539767	.0791646	8.40	0.000	1.392169	1.703014
ssi	1.696737	.1024521	8.76	0.000	1.507362	1.909905
homeless_or_supported	1.687269	.159235	5.54	0.000	1.402338	2.030093
weekwithatleast2calls	2.892232	.1355777	22.66	0.000	2.638347	3.170549
pain	1.546471	.0783568	8.60	0.000	1.400273	1.707932
respiratory	1.606196	.0936261	8.13	0.000	1.432786	1.800593
no_op_atall	4.518399	.190084	35.85	0.000	4.160787	4.906747
age_18to29	1.219486	.060522	4.00	0.000	1.106452	1.344068
age_30to39	1.01554	.0450383	0.35	0.728	.9309941	1.107763
age_40to49	.8671333	.0473584	-2.61	0.009	.7791078	.965104
age_50to59	.7740137	.0407774	-4.86	0.000	.6980794	.858208
age_60to69	.6102234	.0508315	-5.93	0.000	.5183033	.7184453
_cons	.0372867	.0035361	-34.68	0.000	.030962	.0449033

Note: _cons estimates baseline odds.

Condensing complex information into something easily interpreted and actionable: how do we get from A to B?

High risk clients for outreach, 10/31/2018

Jack Jones	Risk score: **10**
Diane Dayton	Risk score: **8**

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Hypothetical client: "Harry Potter"	Response		Odds ratio		Subtotal
No recent mental health outpatient history (last 120 days)?	Yes (1)	*	4.518399	=	4.518399
Multiple SPMI diagnoses (last 12 months)?	No (0)	*	4.334528	=	0
Substance use history (last 12 months)?	Yes (1)	*	2.928598	=	2.928598
Week with 2+ crisis line calls (last 3 weeks)?	Yes (1)	*	2.892232	=	2.892232
SSI for disability (any time)?	No (0)	*	1.696737	=	0
History of housing instability (any time)?	Yes (1)	*	1.687269	=	1.687269
Primary respiratory complaint at healthcare visit (last year)?	No (0)	*	1.606196	=	0
Primary pain complaint at healthcare visit (last year)?	No (0)	*	1.546471	=	0
Constant term	1	*	0.0372867	=	0.0372867
Subtotal				=	**12.0637847**
Scaling to range of 0 to 10	**Subtotal**	/	**2.124772**	=	**6**

Final score

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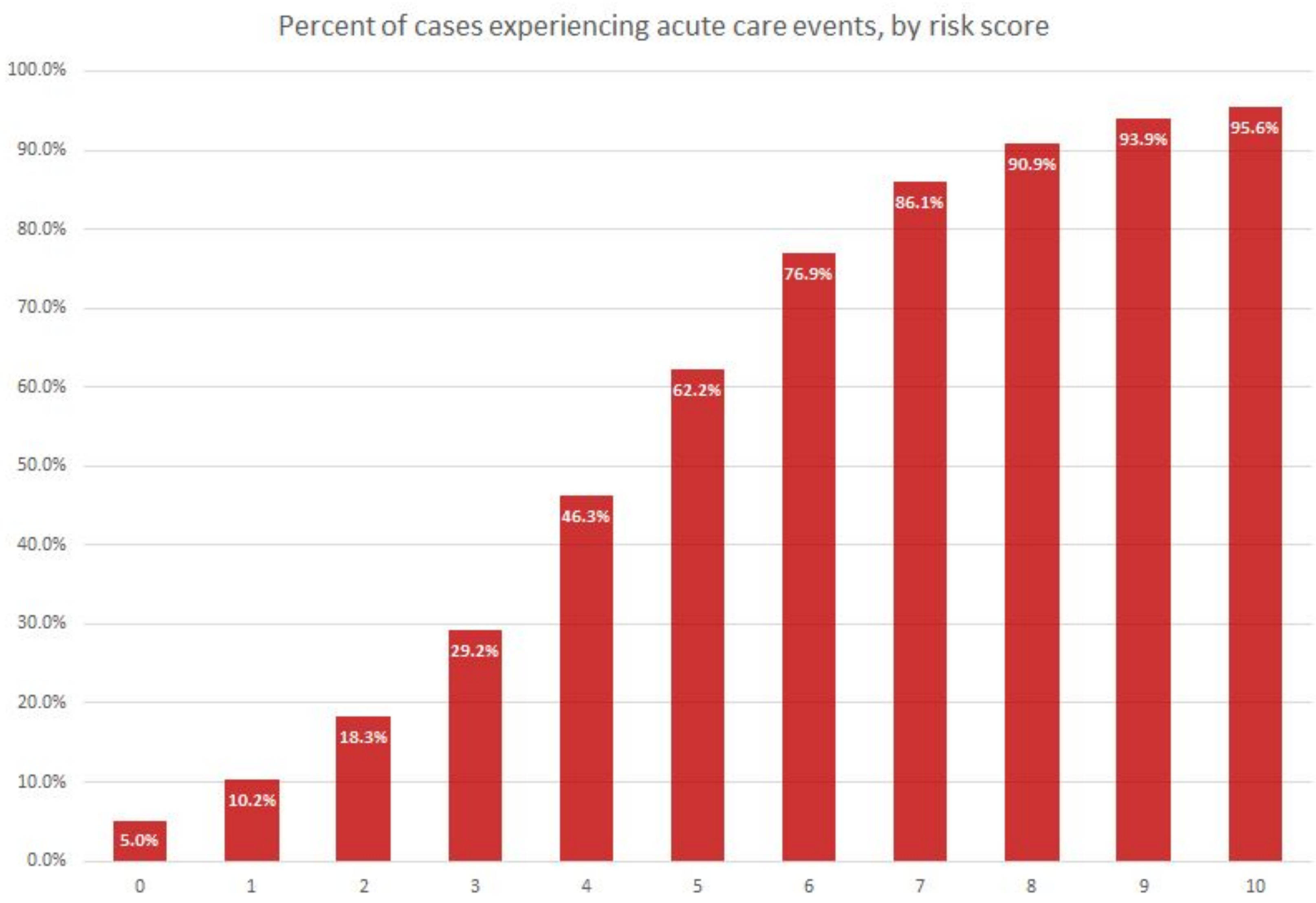
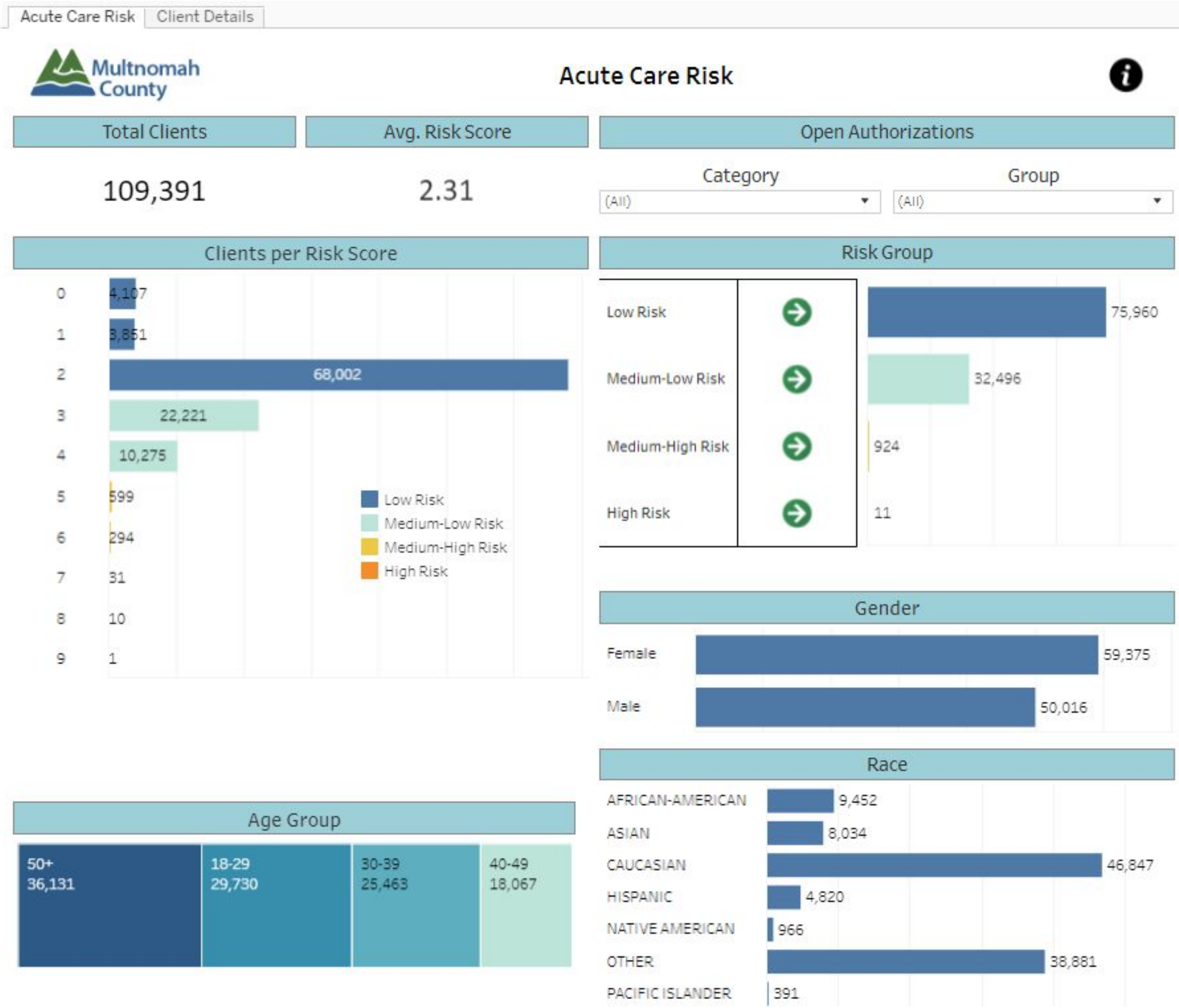


Building the tool

- We have a score--now how do we use it?
  - Automated stored SQL procedure; updated every 24 hours
  - Information available to staff via a Tableau dashboard
    - Look up specific members individually, view all members enrolled in a certain type of services, view members by risk level (e.g., list of all of today's high risk members), explore population averages for different demographics or types of services…
  - Clarity on ethics
    - Only proactively offering help/services, not denying; respecting client autonomy; not intended to override clinical judgment
    - Human behavior too nuanced, messy to reduce to a single number; only intended as an additional data point to help inform


Acute Care Risk
Client Details
Multnomah County
Acute Care Risk
Total Clients
109,391
Avg. Risk Score
2.31
Open Authorizations
Category
(All)
Group
(All)
Clients per Risk Score
0 4,107
1 3,851
2 68,002
3 22,221
4 10,275
5 599
6 294
7 31
8 10
9 1
Low Risk
Medium-Low Risk
Medium-High Risk
High Risk
Risk Group
Low Risk 75,960
Medium-Low Risk 32,496
Medium-High Risk 924
High Risk 11
Gender
Female 59,375
Male 50,016
Race
AFRICAN-AMERICAN 9,452
ASIAN 8,034
CAUCASIAN 46,847
HISPANIC 4,820
NATIVE AMERICAN 966
OTHER 38,881
PACIFIC ISLANDER 391
Age Group
50+ 36,131
18-29 29,730
30-39 25,463
40-49 18,067

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Acute Care Risk | Client Details

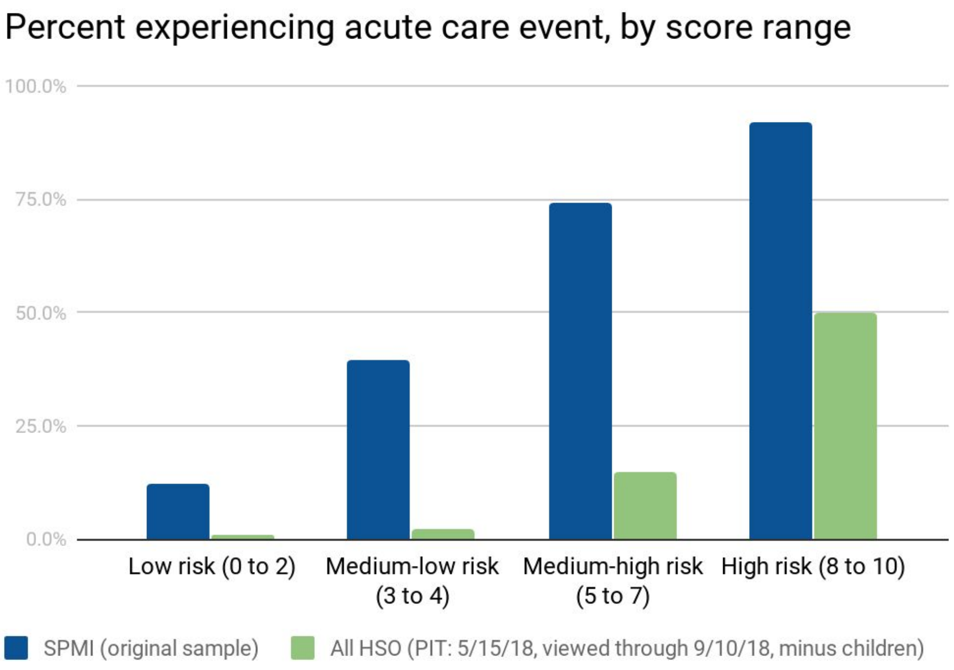
Multnomah County

Policy Id	Full Name	Score	Phone	Gender	Race	Age Group
ABC123	LEIA ORGANA SOLO	5	123-456-7890	Female	WHITE	50+
DEF456	TYRION LANNISTER	7	234-567-8901	Male	OTHER	30-39
GHI789	HERMIONE GRANGER	5	345-678-9012	Female	AFRICAN-AMERI...	18-29
JKL012	ARAGORN S O ARATHO...	6	456-789-0123	Male	WHITE	50+
MNO345	KVOTHE ARLIDENSON	7	Null	Male	OTHER	18-29
PQR678	SHURI	5	567-890-1234	Female	AFRICAN-AMERI...	Under 18
STU901	RA S AL GHUL	7	678-901-2345	Male	ASIAN	40-49

Authorization Type	Referral Id	Vendor Nm	Elig Eff Date
GLOBAL - Level B Adult Global - Primary A...	RESIST999	Lifeworks Northwest	1/1/2014
Outpatient SUD 1/1/17 - Medication Assi...	WESTER999	CODA CD	2/15/2014
Null	Null	Null	3/31/2015
Null	Null	Null	4/1/2015
Null	Null	Null	5/15/2016
Null	Null	Null	6/30/2016
Exceptional Needs - Supported Employm...	GOTHAM999	Cascadia Behavioral Health	7/1/2017

Going “live” with entire population

- One more test: how will this work in the “real world”?
  - If someone used the score today, how accurate would it be?
    - Track actual events for next 30 days; use score as main predictor
    - Predictive power fell to 0.77 → still acceptable, but not as good
- Up to present day; implementation phase



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