Impact of behavioral science-based electronic health record tools on deprescribing for older adults

NIH Pragmatic Trials Collaboratory Grand Rounds
April 2026

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Conflicts of interest

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Potentially inappropriate medication use is a significant problem in older adults

- Potentially-inappropriate medications, like benzodiazepines, non-benzodiazepine sedative hypnotics, and strongly anticholinergic medications are overprescribed in older adults – 20% are using them regularly
  - The vast majority are **long-term users**
  - Long-term use is associated with a 30% increased risk of hospitalizations and falls
- Clinical guidelines, such as the American Geriatrics Society® Beers Criteria, strongly recommend avoiding or limiting the use of these medications

SOURCE: Billioti de Gage S et al BMJ 2014; Hill KD et al Drugs Aging 2014; Ng BJ et al Drugs Aging 2018; Coupland CAC et al JAMA Intern Med 2019

Deprescribing of potentially inappropriate medication is challenging

- Numerous perceived barriers to deprescribing of potentially inappropriate medication
  - Some examples: tendency to maintain status quo, time constraints, patient preferences, diffusion of responsibility
- Physicians also often lack necessary tools or opportunities for deprescribing these medications, especially primary care physicians (PCPs)
- Existing deprescribing interventions are highly resource intensive
- Finding practical, scalable approaches to addressing deprescribing is critical

SOURCE: Billioti de Gage S et al BMJ 2014; Hill KD et al Drugs Aging 2014; Ng BJ et al Drugs Aging 2018; Coupland CAC et al JAMA Intern Med 2019

Electronic health record (EHR)-based approaches have potential to help with deprescribing but may need refinement

- A 2025 systematic review of deprescribing interventions identified 31 trials of EHR software
  - Only 9 used EHR-embedded tools and only 8 were in the US
  - None tested EHR tools in primary care without other patient-facing components

- **Several contributing factors to limited effectiveness of EHR tools in other settings**
  - Clinician alert fatigue
  - Clinical inertia
  - Persuasiveness of the content
  - When they fire in workflow
  - **Absence of necessary functionality**

Could be improved with behavioral science techniques

Many ways to potentially optimize EHR tools with behavioral science

Yet, limited research available for which is most effective → NUDGE-EHR & NUDGE-EHR-2

Source: Persaud N et al. JNO 2025; Liao JM et al. Healthcare 2016; Maddox TM JAMA Cardiol 2020; Thillainadesan J et al Drugs Aging 2018

(NUDGE-EHR) Novel Uses of adaptive Designs to Guide provider Engagement in EHRs 16-arm adaptive trial: PRECURSOR

- **First conducted a 16-arm two-stage adaptive pragmatic trial** among 216 PCPs and their older adult patients with long-term use of these medications
  - Atrius Health (MA), October 2020- August 2022
  - Examined promising EHR deprescribing tools (out of 14 possible)
    - Incorporated 9 different behavioral principles (7 directly tested)
    - Tools varied based on timing of EHR tools (including medication ordering), types, and content
    - Evaluation based on impact of behavioral principles within EHR tools

SOURCE: Design: Lauffenburger JC et al *Imp Sci* 2021; Results: Lauffenburger JC et al *J Am Geriatr Soc* 2025

NUDGE-EHR Trial: Precursor 16-arm adaptive trial

7 behavioral science principles directly tested within the 16 EHR arms

Arm	Alert type	Timing: order entry (X) vs. open encounter	Follow-up booster	Cold state outreach	Simplification language in alert	Sign-off moment	Pre-commitment language in alert	Different presented risks in alert
1	Enhanced	X						
2	Enhanced							
3	Enhanced	X	X					
4	Enhanced		X					
5	Enhanced	X		X				
6	Enhanced			X				
7	Enhanced	X			X			
8	Enhanced				X			
9	Enhanced	X				X		
10	Enhanced					X		
11	Enhanced	X					X	
12	Enhanced						X	
13	Enhanced	X						X
14	Enhanced							X
15	Basic	X						
16	None							

NUDGE-EHR Trial: Precursor 16-arm pragmatic adaptive trial

Stage 1: Adaptive Trial
Oct 2020-Aug 2021

Randomize primary care providers (PCPs) to active arm or usual care

Stratified 201 eligible PCPs into blocks (n=8 to each of Arms 1-15, n=81 to Arm 16)

Arm 1: Order entry alert	Arm 2: Open encounter alert	Arm 3: Order entry alert + follow-up message	Arm 4: Open encounter alert + follow-up message	Arm 5: Order entry alert + pre-visit message	Arm 6: Open encounter alert + pre-visit message	Arm 7: Simplified order entry alert	Arm 8: Simplified open encounter alert	Arm 9: Order entry alert + sign off alert	Arm 10: Open encounter alert + sign-off alert	Arm 11: Pre-commitment alert + Order entry alert	Arm 12: Pre-commitment alert + Open encounter alert	Arm 13: Order entry alert with different risk presentation	Arm 14: Open encounter alert with different risk presentation	Arm 15: Non-enhanced standard alert	Arm 16: Usual care (no alert or intervention)

Interim Analysis

Stage 2: Adaptive Trial
Sept 2021-Aug 2022

Re-randomize to one of the top 5 most successful arms identified in Stage 1 or to Usual care

Arm 2: Open encounter alert (n=27)	Arm 4: Open encounter alert + follow-up message (n=27)	Arm 8: Simplified open encounter alert (n=28)	Arm 10: Open encounter alert + sign-off alert (n=28)	Arm 12: Pre-commitment alert + Open encounter alert (n=27)	Arm 16: Usual care (no alert or intervention) (n=60)

Final Analysis

Evaluate outcomes after additional 9-month follow-up

The two most promising EHR tools were selected for this parallel group trial: NUDGE-EHR-2

NUDGE-EHR-2 trial:
Do behavioral science-informed EHR tools improve deprescribing of potentially-inappropriate medications in older adults?

- Conducted at a different health system (Mass General Hospital) than the precursor trial, November 2022 – March 2024
- 3-arm parallel arm pragmatic trial of PCPs cluster randomized to:
  - **Arm 1 ("Pre-commitment"):** PCPs received an EHR alert recommending discussion of medication risks at the first patient visit and at the second visit, received an alert that encouraged deprescribing
    - Precursor trial: 20% relative increase in deprescribing
  - **Arm 2 ("Boostering"):** PCPs received an EHR alert encouraging deprescribing at the first patient visit and a reminder in their in-basket four weeks later
    - Precursor trial: 15% relative increase in deprescribing
  - **Arm 3 ("Usual care"):** No tool

SOURCE: Lauffenburger JC et al JAMA 2026

NUDGE-EHR-2 Trial design

- Eligibility determined during the trial:
  - Adults ≥65 years
  - Prescribed ≥90 pills of benzodiazepine, sedative hypnotic, or two anticholinergic medications in the last 180 days
  - Office or telemedicine visit with a randomized PCP
- Waiver of informed consent and authorization of study data for both PCPs and patients

Example EHR tool: Pre-commitment Arm 1
First visit

Your patient has been prescribed at least 90 pills of a benzodiazepine in the past 6 months. Benzodiazepines **increase a patient's risk of falling in the next year by 30%**. Patients who have fallen are 75% less able to perform all their activities of daily living.

Almost all older adults can be safely tapered off these medications. **Will you start by sharing the handout below with your patient and then discussing a taper at your next appointment?**

Collapse

If your patient is ready to taper now, use the SmartSet below to generate a benzodiazepine taper.

Click here to view or print patient handout on how to taper off benzodiazepines – use .benzoinfo to add handout to patient instructions in the after-visit summary

Open SmartSet | Do Not Open | **Preset benzodiazepine taper / Alternative options / Pt instructions** Preview

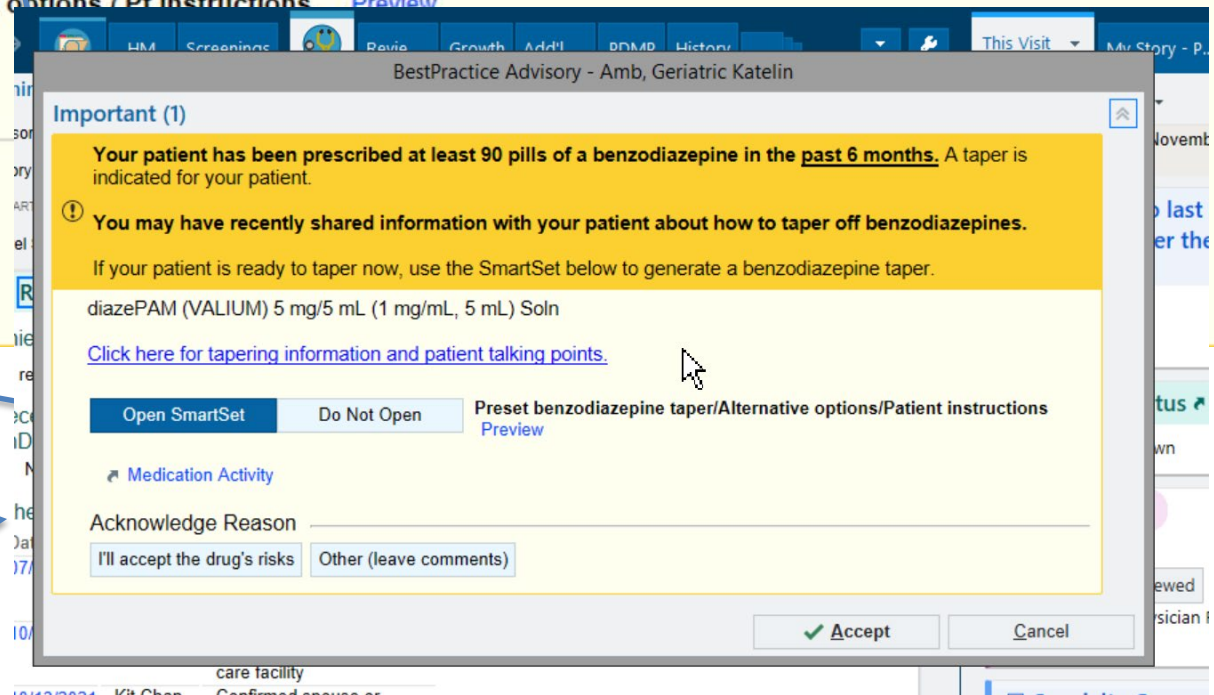
Medication Activity

Acknowledge Reason

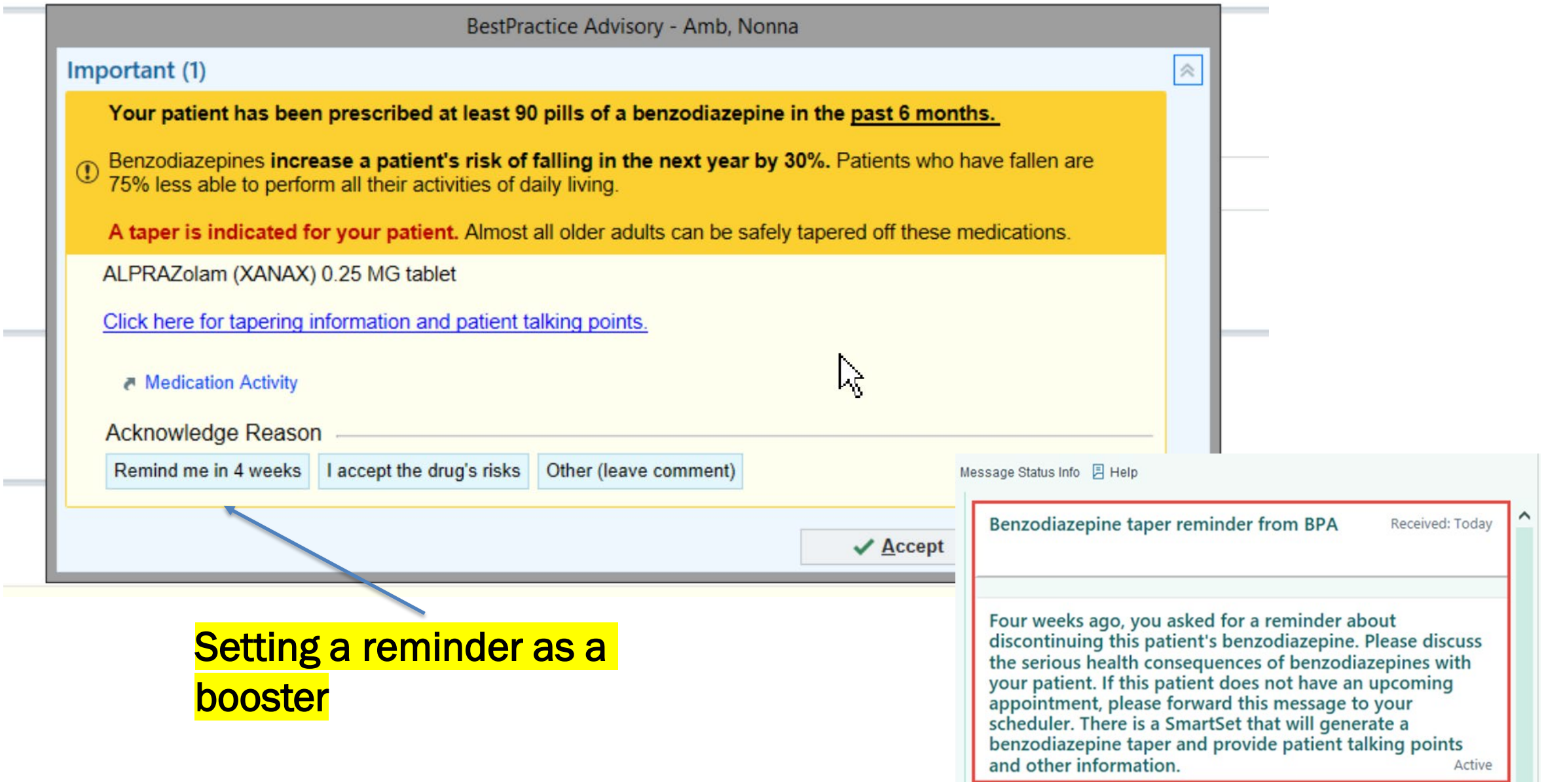
I shared patient handout | I'll accept the drug's risks | Other (leave comment)

✔ Accept (1)

2nd visit



Example EHR tool: Boostering Arm 2



Setting a reminder as a booster

Other common components of the EHR tools

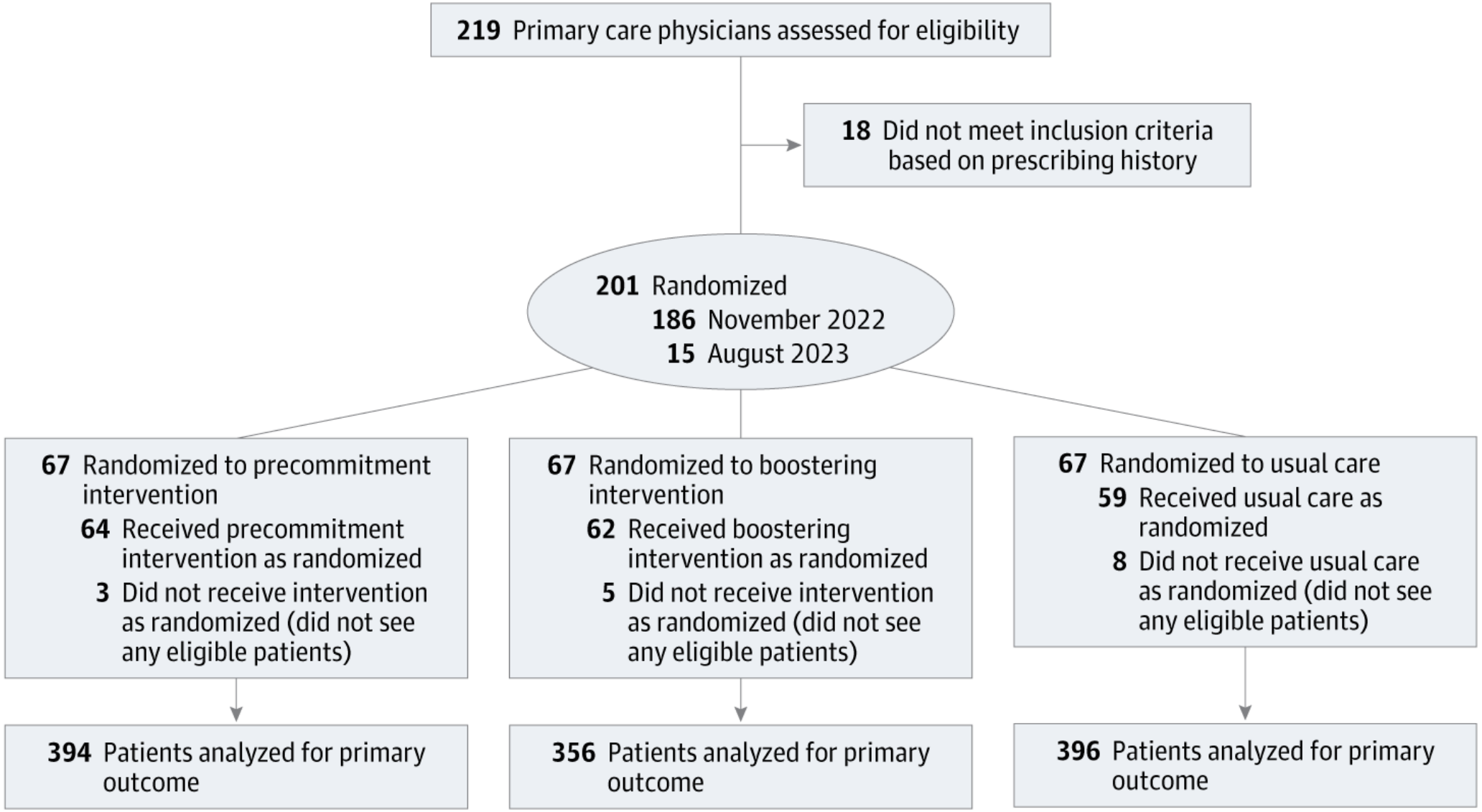
- **SmartSet including:**
  - Customizable tapering algorithms based on guidelines
  - Patient instructions that can be added to after-visit summary
    - Customizable instructions for tapering
    - Managing insomnia and/or anxiety
  - Orders for medication alternatives
  - Referrals to behavioral health
- **Tips for providers to discuss deprescribing with patients**

Outcome evaluation

Type	Outcome	Data source	Definition
Primary	Reduction in prescribing (patient level)	Electronic health records	Composite of: 1) discontinuation of ≥1 medication and no subsequent order, 2) absence of an order over follow-up, and 3) ordering a dose taper between the patient's index date and end of follow-up
Secondary	Cumulative prescribing (patient level)	Electronic health records	a) Cumulative lorazepam milligram equivalents prescribed per patient (benzos/Z-drugs) b) Cumulative pills prescribed per patient

- Generalized estimating equations with a log link and binary-distributed errors, adjusting for physician-level clustering
- Designed to detect an absolute effect size of 10% between each of the two intervention arms and usual care, assuming usual care=25% and ICC=0.1, at >80% power and adjusting for multiple testing

Identification and enrollment



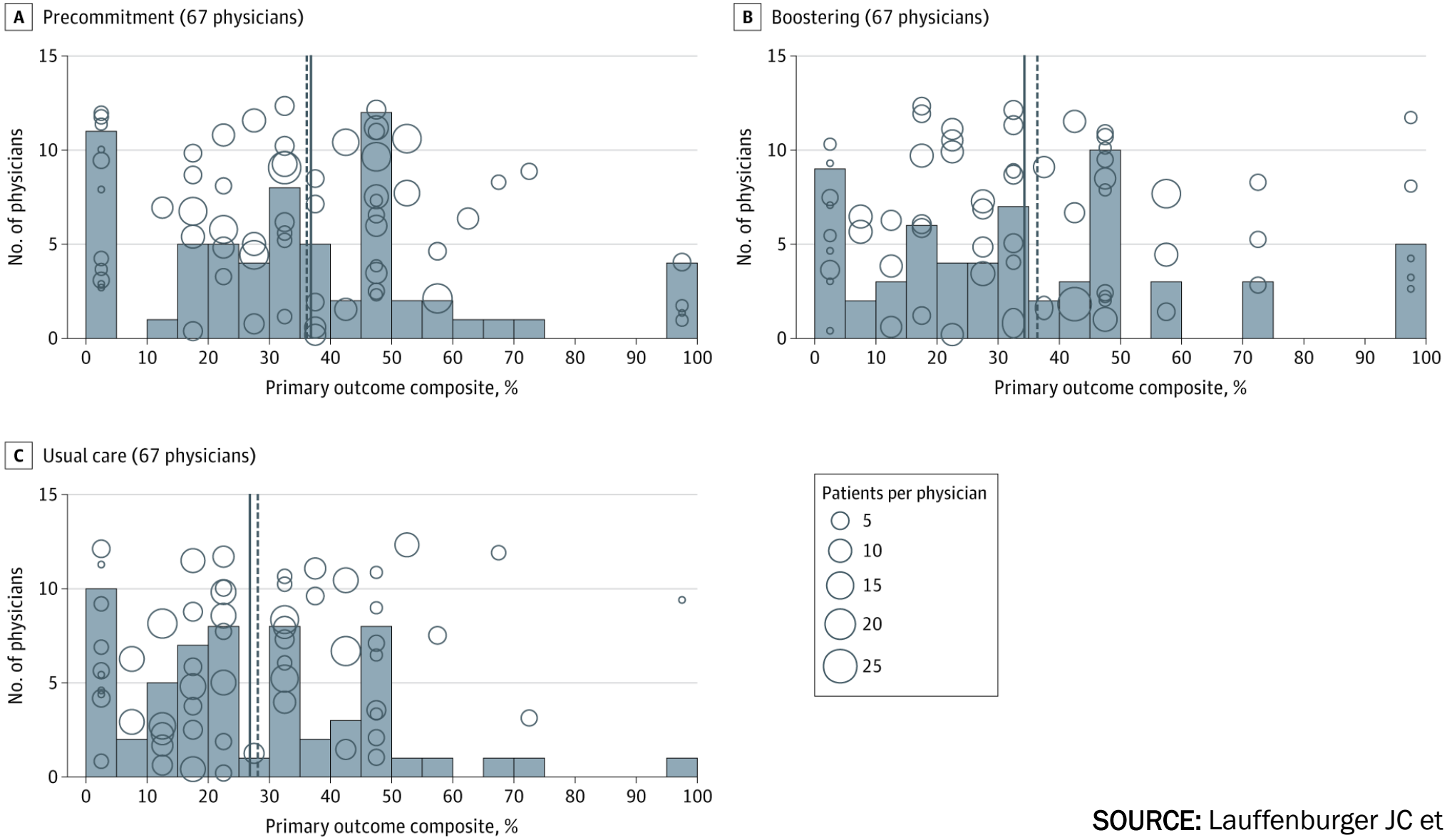
Length of follow-up:	Mean: 291 (SD: 145) days	Mean: 298 (SD: 142) days	Mean: 281 (SD: 136) days

SOURCE: Lauffenburger JC et al JAMA 2026

Baseline characteristics

	Arm 1: Pre-commitment intervention	Arm 2: Boostering intervention	Arm 3: Usual Care
No. of eligible patients/PCP mean (SD)	5.9 (4.9)	5.3 (4.4)	5.9 (4.8)
Patient Characteristics			
Age, mean (SD)	73.7 (6.5)	73.6 (6.5)	73.5 (6.4)
Female sex, N (%)	276 (70.1)	248 (69.7)	275 (69.4)
White race, N (%)	347 (88.1)	298 (83.7)	350 (88.4)
Hispanic ethnicity, N (%)	26 (6.6)	33 (9.3)	21 (5.3)
Benzodiazepine eligible, N (%)	212 (53.8)	183 (51.4)	221 (55.8)
Z-drug eligible, N (%)	37 (9.4)	14 (3.9)	22 (5.6)
Anticholinergic eligible, N (%)	299 (75.9)	279 (78.4)	283 (71.5)
Multiple classes, N (%)	145 (36.8)	116 (32.6)	124 (31.3)

Effect by individual physician performance on the primary deprescribing outcome on average across patients



SOURCE: Lauffenburger JC et al JAMA 2026

Both types of EHR interventions were effective on deprescribing

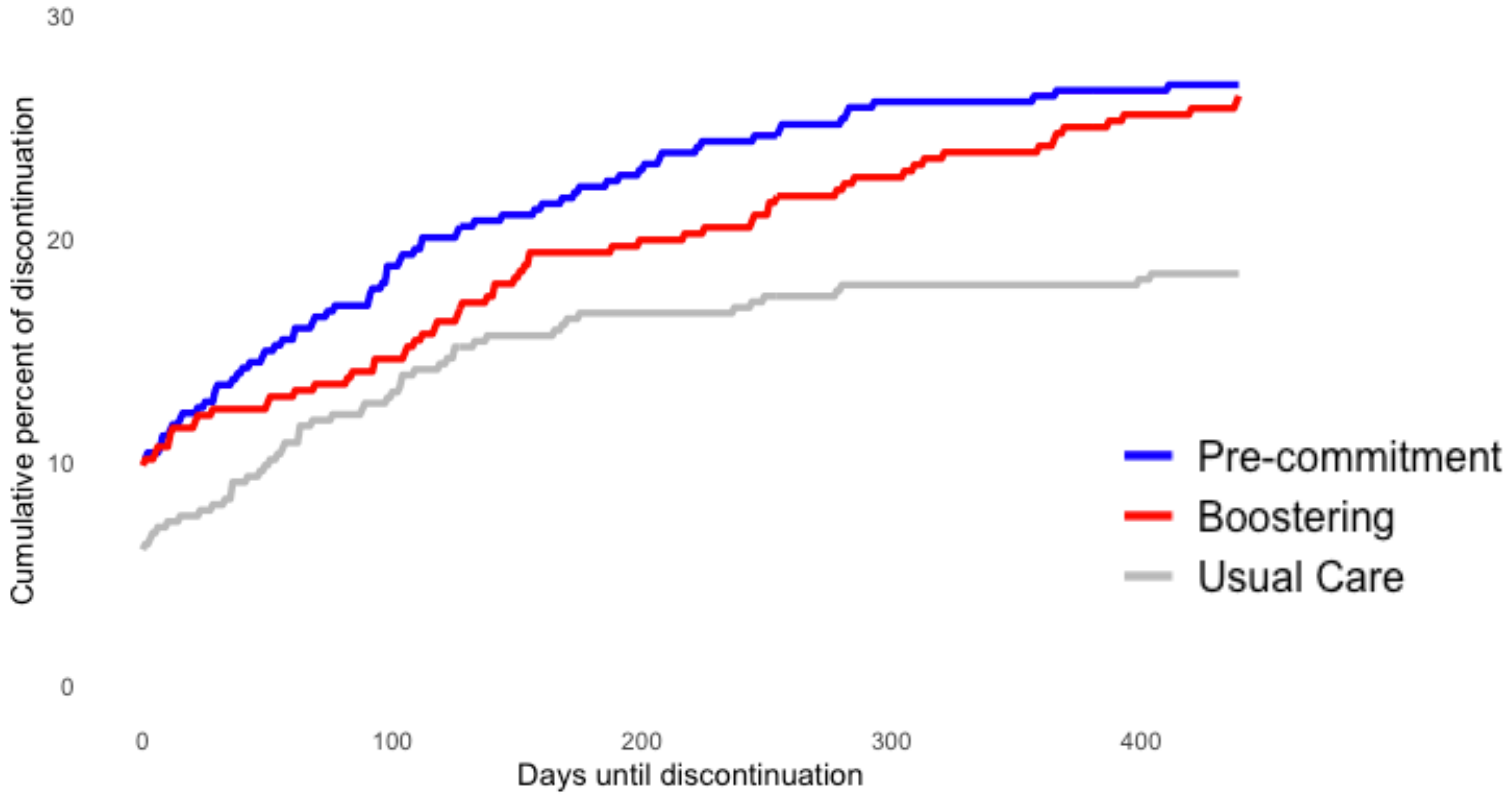
Table 2. Patient-Level Results for the Primary Outcome

Primary outcome composite	No. (%) of patients			Absolute difference, %		Relative risk (95% CI)	
	Precommitment intervention (n = 394)	Boostering intervention (n = 356)	Usual care (n = 396)	Precommitment vs usual care	Boostering vs usual care	Precommitment vs usual care	Boostering vs usual care
Primary analysis	145 (36.8)	122 (34.3)	106 (26.8)	10.4	6.5	1.40 (1.14-1.73)	1.26 (1.01-1.57)
Prespecified secondary analyses of the primary outcome							
Adjusted for patient age, race, ethnicity, and sex	145 (36.8)	122 (34.3)	106 (26.8)	10.3	5.9	1.41 (1.14-1.74)	1.26 (1.01-1.58)
No. of medication classes							
1 (n = 761)	92 (36.9)	80 (33.3)	67 (24.6)	13.9	9.1	1.58 (1.23-2.03)	1.35 (1.03-1.76)
>1 (n = 385)	53 (36.6)	42 (36.2)	39 (31.5)	3.6	1.8	1.10 (0.81-1.49)	1.11 (0.78-1.56)

Increased deprescribing by 6.5% to 10.4% absolute percentage points versus usual care

SOURCE: Lauffenburger JC et al JAMA 2026

Active discontinuation by PCPs appeared to drive the effect



Primary outcome components adjusted for multiple testing	Pre-commitment intervention	Boostering intervention	Usual care	Pre-commitment vs. Usual Care Relative risk (95% CI)	Boostering vs. Usual Care Relative risk (95% CI)
Active discontinuation	106 (26.9%)	94 (26.4%)	73 (18.4%)	1.49 (1.15 – 1.92)	1.44 (1.12 – 1.86)
Passive discontinuation	57 (14.5%)	41 (11.5%)	47 (11.9%)	1.18 (0.79 – 1.75)	0.94 (0.63 – 1.40)
Dose taper	5 (1.3%)	2 (0.6%)	2 (0.5%)	2.62 (0.58 – 11.77)	1.20 (0.16 – 8.85)

No significant effect modification in pre-specified subgroup analyses

Outcomes	Pre-commitment intervention vs. Usual Care (Relative risk [95% CI]), Absolute difference			Boostering intervention vs. Usual Care Relative risk [95% CI]), Absolute difference		
Sex subgroups	Female	Male	Interaction p-value	Female	Male	Interaction p-value
Primary outcome composite	1.46 (1.11 – 1.92), 11.3%	1.21 (0.20 – 7.25), 4.3%	0.183	1.33 (1.02 – 1.75), 8.7%	0.93 (0.62 – 1.39), -2.3%	0.229
Race subgroups	White	Non-White[§]	Interaction p-value	White	Non-White[§]	Interaction p-value
Primary outcome composite	1.41 (1.13 – 1.75), 10.5%	1.86 (1.06 – 3.27), 12.3%	0.751	1.25 (0.99 – 1.58), 6.7%	1.32 (0.72 – 2.44), 6.3%	0.741
Ethnicity subgroups	Non-Hispanic/Latino	Hispanic/Latino	Interaction p-value	Non-Hispanic/Latino	Hispanic/Latino	Interaction p-value
Primary outcome composite	1.43 (1.16 – 1.76), 10.9%	1.66 (0.80 – 3.46), 10.1%	0.586	1.22 (0.97 – 1.53), 5.2%	*	*

*too small to compute

[§] Includes all other patient races (i.e., Asian, Black, Other)

Abbreviations: CI, Confidence Interval

The effect of the EHR tools on the primary outcome were robust to other types of analyses

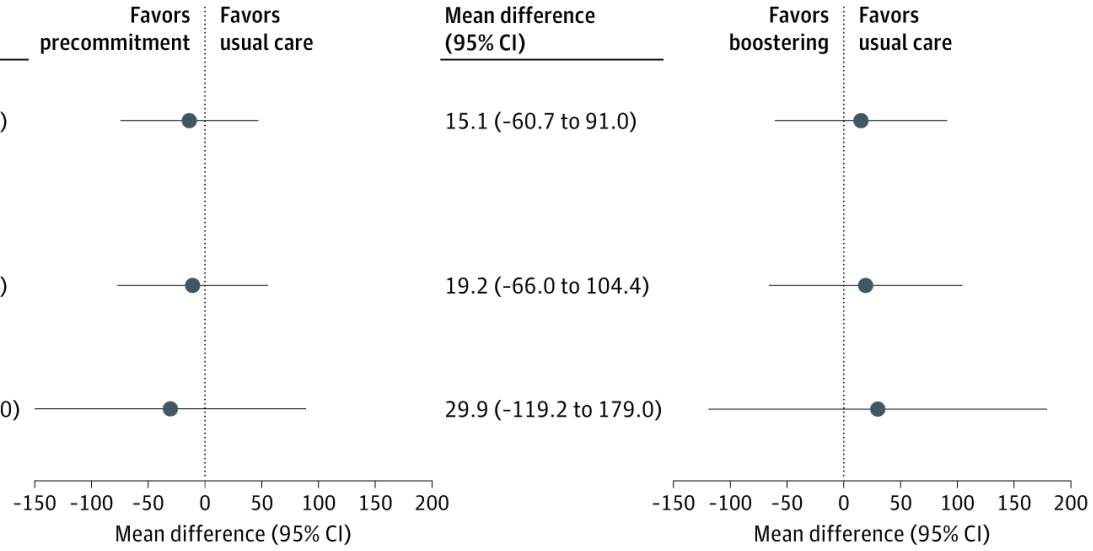
Outcome	Pre-commitment intervention	Boostering intervention	Usual care	Pre-commitment vs. Usual Care Relative risk (95% CI)	Boostering vs. Usual Care Relative risk (95% CI)
Sensitivity analyses					
Adjusted for calendar time	145 (36.8%)	122 (34.3%)	106 (26.8%)	**1.68 (1.22 – 2.30)**	**1.30 (1.06 – 1.61)**
Adjusted for baseline characteristics	145 (36.8%)	122 (34.3%)	106 (26.8%)	**1.41 (1.14 – 1.74)**	**1.26 (1.01 – 1.58)**
Discontinuation for ≥90 days (no resumption) (n=1146)	152 (41.4%)	127 (39.7%)	114 (32.3%)	**1.31 (1.07 – 1.60)**	**1.21 (1.00 – 1.48)**
Restricting to patients with ≥90 days of follow-up (n=1008)	115 (33.4%)	99 (31.0%)	82 (23.8%)	**1.44 (1.13 – 1.84)**	**1.29 (1.01 – 1.66)**
Stratified analyses					
By number of total patients seen by PCP					
≤5 patients (n=288)	39 (38.6%)	38 (43.7%)	30 (30.0%)	1.22 (0.84 – 1.76)	**1.45 (1.02 – 2.05)**
>5 patients (n=858)	106 (36.2%)	84 (31.2%)	76 (25.7%)	**1.48 (1.16 – 1.90)**	1.25 (0.95 – 1.64)
By medication class					
Benzodiazepines (n=616)	65 (30.7%)	50 (27.3%)	45 (20.4%)	**1.46 (1.07 – 2.00)**	1.32 (0.95 – 1.85)
Sedative hypnotics (n=73)	11 (29.7%)	6 (42.9%)	8 (36.4%)	1.02 (0.56 – 1.85)	*
Anticholinergics (n=861)	125 (41.8%)	108 (38.7%)	94 (33.2%)	**1.26 (1.03 – 1.56)**	1.14 (0.91 – 1.42)

* too small to compute

No significant effect of the EHR tools on the secondary outcomes

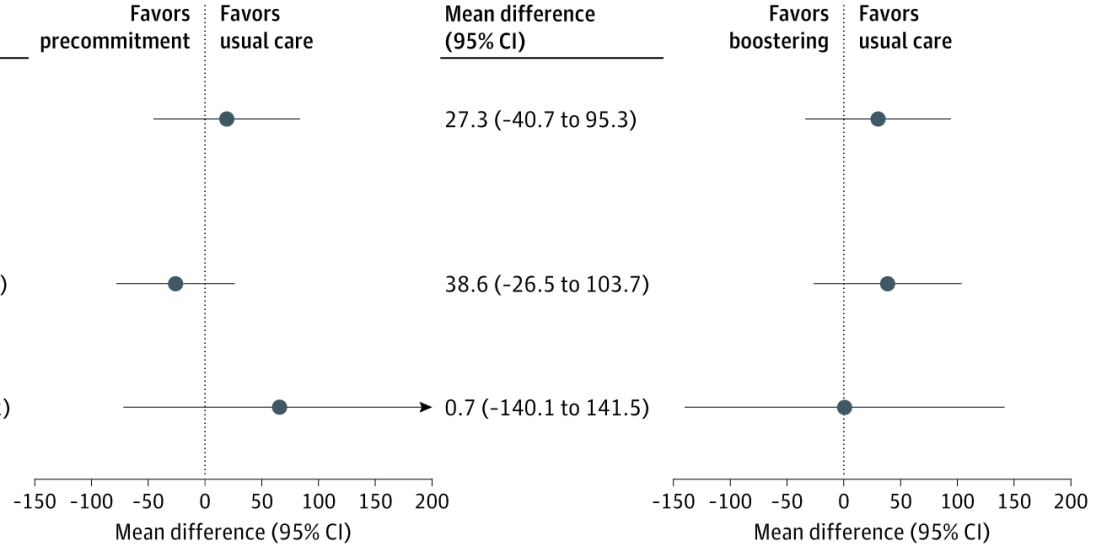
A Cumulative lorazepam milligram equivalents prescribed per patient

	Precommitment (n = 394)	Boostering (n = 356)	Usual care (n = 396)	Mean difference (95% CI)	Mean difference (95% CI)
Primary analysis					
Mean (SD)	220.1 (413.9)	259.7 (601.3)	238.7 (461.6)	-13.8 (-74.5 to 47.0)	15.1 (-60.7 to 91.0)
Median (IQR)	6.8 (0 to 249)	0 (0 to 270)	15 (0 to 287)		
Prespecified secondary analyses					
Stratified by 1 medication class					
Mean (SD)	165.0 (385.1)	206.9 (625.5)	179.5 (352.6)	-10.9 (-77.1 to 55.3)	19.2 (-66.0 to 104.4)
Median (IQR)	0 (0 to 229)	0 (0 to 120)	0 (0 to 135)		
Stratified by >1 medication class					
Mean (SD)	314.8 (444.7)	368.8 (534.1)	368.4 (621.0)	-30.5 (-150.0 to 89.0)	29.9 (-119.2 to 179.0)
Median (IQR)	120 (8.8 to 440)	168 (0 to 522)	120 (15 to 405)		



B Cumulative pill quantity of potentially inappropriate medication prescribed per patient

	Precommitment (n = 394)	Boostering (n = 356)	Usual care (n = 396)	Mean difference (95% CI)	Mean difference (95% CI)
Primary analysis					
Mean (SD)	401.1 (468.1)	417 (479.1)	386.5 (438.1)	19.2 (-45.2 to 83.5)	27.3 (-40.7 to 95.3)
Median (IQR)	258.5 (90 to 558.8)	271 (90 to 540)	227.5 (900 to 540)		
Prespecified secondary analyses					
Stratified by 1 medication class					
Mean (SD)	283.5 (299.1)	345 (403.4)	306 (347.6)	-25.9 (-78.0 to 26.2)	38.6 (-26.5 to 103.7)
Median (IQR)	180 (60 to 450)	240 (90 to 450)	180 (90 to 392.5)		
Stratified by >1 medication class					
Mean (SD)	603.1 (615.6)	565.9 (580.8)	563.1 (551.7)	65.7 (-71.9 to 203.2)	0.7 (-140.1 to 141.5)
Median (IQR)	450 (180 to 810)	343 (172.5 to 780.5)	391 (127.5 to 817.5)		



Summary

- Deploying low-touch EHR tools for PCPs when opening charting for a patient visit, paired with approaches specifically designed to support deprescribing longitudinally, meaningfully improves deprescribing
  - Pre-commitment likely laid the groundwork for future deprescribing conversations
  - Boostering likely worked by delivering reminders outside the immediate demands of patient care
- Deprescribing rate somewhat higher than prior efficacy studies, likely due to broader inclusion and reach
- No impact on the secondary outcome possibly because of substitution effects and large CIs

Implications

- Behavioral science-based EHR tools are a practical, scalable approach to addressing deprescribing
- EHR tools are likely to be one piece of potential deprescribing interventions
  - Original RFA requested research on behavioral economics principles for interventions in EHRs for improving physician compliance with guidelines
- This multi-trial process also highlights the value of using pre-selection approaches to behavioral interventions with confirmation in traditional trials

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List of study medications

Medication class	Medicine name (generic name)
Benzodiazepines	Alprazolam, Chlordiazepoxide, Clonazepam, Diazepam, Estazolam, Flurazepam, Lorazepam, Oxazepam, Temazepam, Triazolam
Non-benzodiazepine sedative hypnotics	Eszopiclone, Zaleplon, Zolpidem
Anticholinergics	Amitriptyline, Baclofen, Cyclobenzaprine, Doxepin, Hydroxyzine, Loratadine, Meclizine, Nortriptyline, Olanzapine, Oxybutynin, Paroxetine, Sertraline, Solifenacin, Tizanidine

Deaths and serious adverse events reported

Group	Number of deaths	Percentage of study group	Number of serious adverse events	Percentage of study group
Pre-commitment intervention	6	1.4%	0	0.0%
Boostering intervention	14	3.9%	0	0.0%
Usual care	7	1.8%	0	0.0%

Note: Serious adverse events were collected through adverse event reporting data by providers and staff, as pre-specified in the statistical analysis plan