




Review

Predictive model-based interventions to reduce outpatient no-shows: a rapid systematic review

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ABSTRACT

Objective: Outpatient no-shows have important implications for costs and the quality of care. Predictive models of no-shows could be used to target intervention delivery to reduce no-shows. We reviewed the effectiveness of predictive model-based interventions on outpatient no-shows, intervention costs, acceptability, and equity.

Materials and Methods: Rapid systematic review of randomized controlled trials (RCTs) and non-RCTs. We searched Medline, Cochrane CENTRAL, Embase, IEEE Xplore, and Clinical Trial Registries on March 30, 2022 (updated on July 8, 2022). Two reviewers extracted outcome data and assessed the risk of bias using ROB 2, ROBINS-I, and confidence in the evidence using GRADE. We calculated risk ratios (RRs) for the relationship between the intervention and no-show rates (primary outcome), compared with usual appointment scheduling. Meta-analysis was not possible due to heterogeneity.

Results: We included 7 RCTs and 1 non-RCT, in dermatology ($n=2$), outpatient primary care ($n=2$), endoscopy, oncology, mental health, pneumology, and an magnetic resonance imaging clinic. There was high certainty evidence that predictive model-based text message reminders reduced no-shows (1 RCT, median RR 0.91, interquartile range [IQR] 0.90, 0.92). There was moderate certainty evidence that predictive model-based phone call reminders (3 RCTs, median RR 0.61, IQR 0.49, 0.68) and patient navigators reduced no-shows (1 RCT, RR 0.55, 95% confidence interval 0.46, 0.67). The effect of predictive model-based overbooking was uncertain. Limited information was reported on cost-effectiveness, acceptability, and equity.

Discussion and Conclusions: Predictive modeling plus text message reminders, phone call reminders, and patient navigator calls are probably effective at reducing no-shows. Further research is needed on the comparative effectiveness of predictive model-based interventions addressed to patients at high risk of no-shows versus nontargeted interventions addressed to all patients.

Key words: predictive model, decision support system, appointment attendance, no-show, missed appointment

BACKGROUND

No-shows (ie, missed appointments without prior notification to the healthcare provider) are a significant challenge for healthcare systems, with implications for costs, patient waiting times, and quality of care. The global average no-show rate is 23%, but rates vary geographically and among medical specialties, ranging from 43% across Africa to 13% across Oceania.¹ In 2019/2020, there were 5 656 365 outpatient no-shows across the National Health Service (NHS) in the United Kingdom,² with an estimated annual cost as high as £750 million.³ Outpatient no-shows are associated with worse health outcomes⁴ and are an independent predictor of increased subsequent acute care utilization.^{5,6}

Outpatient no-shows are a complex, multifactorial phenomenon, associated with patient characteristics, including demographics relevant to equity (eg, receipt of welfare payments, travel time to appointment) and characteristics of the appointment and the healthcare system (eg, lead time).^{1,4,7,8} Organizational interventions, such as overbooking, and interventions facilitating access to appointments, such as reminders,^{9–13} transportation to appointments, and financial incentives,¹⁴ have been developed to increase attendance, reduce no-shows, or increase timely cancellations and reschedules. These goals are distinct, and preference for one over the other may depend on the clinical context. For example, in settings where the main driver of no-shows is the resolution of the patient's complaint, timely cancellations could free up appointments for other patients. On the contrary, clinics that work with patients with progressive, disabling disorders may prioritize increased attendance. In terms of effectiveness, reminders increase appointment attendance and reduce no-show rates.^{9–13} Financial incentives may be effective at increasing appointment attendance in some settings,^{15,16} but not in safety-net clinics,¹⁴ and there is mixed evidence on the effect of patient navigators, transportation to appointments, and patient contracts.¹⁴ Overbooking may potentially decrease no-show rates,¹⁷ but there are concerns about the potential impact of overbooking on patients.¹⁸

More recent interventions have attempted to incorporate big data and machine learning. Predictive models that identify appointments at high risk of no-show could complement existing interventions, for instance by guiding the selection of appointments to overbook. They could also serve to select patients for more resource-intensive interventions, such as patient navigators (ie, trained staff contacting patients to help facilitate their care journey).

The study of predictive models of no-shows is timely, because of their increasing availability. A 2020 systematic review identified 50 papers reporting the development of predictive models of no-shows, one-quarter of which had been published in the last 2 years.¹⁹ There is also ample opportunity for real-world implementation of such predictive models. For example, a predictive model of no-shows is included in the electronic health record (EHR) supplied by Epic Systems.²⁰ Over 45% of the US population has an EHR in Epic,²¹ and Epic's EHR is increasingly used in Canada, the European Union, Australia, and the United Kingdom.^{22–24} However, there is no published evidence synthesis on the effectiveness of interventions that include a predictive model to reduce no-shows, and the published review of these models reports no information on cost-effectiveness, acceptability, or equity.

OBJECTIVE

We conducted a rapid systematic review to synthesize the evidence on the effect of predictive model-based interventions on outpatient no-shows, and on costs, acceptability, and equity.

MATERIALS AND METHODS

We conducted a rapid systematic review of controlled trials assessing predictive model-based interventions aiming to reduce outpatient no-shows, to inform decision-making on the implementation of the Epic predictive model in the local context in a timely manner.^{25,26} We structured the review process using the Synthesis Without Meta-analysis (SWiM) guidelines for narrative evidence synthesis, adapted to rapid review.²⁷ The review was prospectively registered (PROSPERO CRD42022321894).²⁸

Data sources and search strategy

We searched Medline, Cochrane CENTRAL, Embase, and IEEE Xplore Digital Library for published studies. We searched ClinicalTrials.gov and the WHO International Clinical Trials Registry Platform (ICTRP) for studies with unpublished results and ongoing studies. We developed a search strategy based on Medical Subject Headings (MeSH) and free search terms used in published reviews of no-shows.^{1,19} The search strategy was initially developed for Medline using Ovid and adapted to IEEE Xplore and Cochrane CENTRAL. Searches were conducted on March 30, 2022. We compared the results with a test set of identified studies and achieved 100% return. We conducted an additional search with broader terms on EMBASE via Ovid on July 8, 2022, to identify any additional studies. The search strategies are in [Supplementary Methods S1](#).

Study selection

Study inclusion criteria were:

- Randomized controlled trials (RCTs), nonrandomized controlled trials, and interrupted time series.
- Assessing interventions based on predictive models and aiming to reduce no-shows or increase attendance, with any comparator.
- Conducted in outpatient care, with adults with any condition.
- Reporting at least 1 outcome domain indicating appointment attendance (ie, no-shows, cancellations, attended appointments).

Study exclusion criteria were:

- Studies lacking a contemporaneous control group (eg, studies using historical or simulated controls), interrupted time series with fewer than 3 data collection points before and 3 after the intervention. Studies lacking a contemporaneous control group were excluded because some of the determinants of no-shows identified in the literature are seasonal. One systematic review reports that determinants of no-shows include the year, season, and month of the appointment.¹ In addition, a systematic review of predictive models of no-shows found that some predictive models used the season and month of the appointment, the weather, and the presence of holidays, as predictor variables of no-shows.¹⁹
- Studies in pediatric settings (ie, participants were under 18 years old according to the inclusion criteria) or in general practitioner offices, and studies focused exclusively on vaccination appointments or population screening. These studies were excluded because vaccination and population screening are single-instance contacts of large portions of the public with the healthcare system. In contrast, outpatient care often concerns repeat appointments with chronically ill patients. Therefore, outpatient care generates datasets of patients' attendance history, which can be used to develop predictive models.

One reviewer screened all abstracts and full texts. A second reviewer independently screened 10% of all abstracts and full texts (agreement rate 99.3%). One reviewer hand-searched the reference lists of all included articles for eligible studies. We retained multiple reports of the same study if they reported different information (eg, sensitivity analyses).

Data extraction and quality assessment

One reviewer extracted data from all included studies using a piloted form, and assessed study quality using the Cochrane Risk of Bias tool (ROB 2) or Risk Of Bias In Nonrandomized Studies of Interventions (ROBINS-I).^{29,30} A second reviewer checked all outcome data and independently assessed study quality. Disagreements were resolved by discussion and arbitration by a senior reviewer. If an included paper cited a previous publication where the predictive model was described, we used that publication in data extraction.

Data extraction included the following information:

- Study design, follow-up duration, comparator, sample size, funding source (private/public/mixed), country, and medical specialty of the trial site.
- Intervention characteristics, drawing on the template for intervention description and replication (TIDieR) items³¹: materials/procedures delivered to increase attendance (eg, phone call reminders), by whom, when, and at which dosage, when and how the predictive model was used to identify high-risk patients for intervention delivery, and, if applicable, any information on intervention tailoring.
- Predictive model characteristics, including information on the dataset and the analysis used for model development and validation (number of appointments, no-show rate, type of analysis, variable selection technique, predictors), and model discrimination and predictive performance measures (eg, *c*-statistic with 95% confidence interval [CI]).
- The following outcomes:
 - We extracted outcome data to calculate the risk ratio (RR) of no-shows as our primary outcome (ie, number of no-shows per arm, number of all appointments per arm). Where possible, we extracted outcome data to calculate the RR of secondary outcomes, including appointment attendance, cancellations, and/or reschedules. Intention-to-treat data were extracted where possible. RRs were calculated as: (number of participants who presented the outcome in question in the intervention group/number of participants assigned to the intervention group)/(number of participants who presented the outcome in question in the control group/number of participants assigned to the control group).
 - A narrative summary of costs and cost-effectiveness analyses, acceptability (defined as any measure of perceptions, feedback, or experience of healthcare professionals, patients, or other stakeholders), and intervention equitability. For the latter outcome, we extracted a narrative summary of any sensitivity analyses of differences in the intervention effect between participant subgroups. We focused on groups defined by the PROGRESS-Plus, which lists characteristics relevant to health equity (age, gender, place of residence, race/ethnicity, language, occupation, religion, education, socioeconomic status).³²

Data synthesis

We grouped results by intervention type. Intervention types were identified from the initial examination and categorization of the

data. A meta-analysis was not conducted due to the incomplete reporting of outcome data and significant heterogeneity in outcome measures. Specifically, no-show RRs at the appointment level could be calculated for only 3 studies, which assessed 3 different interventions (phone call reminders, patient navigator, and text message reminders).³³ However, we present the range of RR (median, interquartile range, and minimum–maximum range). Where it was not possible to calculate RR, we provided a narrative summary of attendance outcomes, as reported in each study. Risk of bias figures was produced using the robvis app.³⁴

We undertook GRADE assessment of the certainty of the evidence for the comparison of each intervention with usual care for the outcomes of no-shows, cancellations, reschedules, and attendance.³⁵ GRADE assessment indicates the degree of confidence that the identified estimate of effect is close to the true quantity, ranging from very low to high. The assessment takes into consideration the risk of bias in the included studies, risk of publication bias in the body of evidence, directness of evidence, heterogeneity, and precision of effect estimates. GRADE assessment was performed by 2 reviewers who reached a consensus on all decisions. Our approach followed Murad 2017 because the evidence did not include pooled effect estimates.³⁶

For each comparison, we presented the following outcomes in a Summary of Findings table: no-shows (main manuscript), cancellations, reschedules, and attendance (appendix). The Summary of Findings table includes information on the quality of the evidence, the magnitude of the effects of the included interventions, and the overall grading of the evidence for each outcome using the GRADE approach.³⁵ We followed the advice of the GRADE working group in the terminology we used to communicate our GRADE assessments of evidence. As such, we use the terms “is effective,” “is probably effective,” and “may be effective” to refer to high, moderate, and low certainty evidence, respectively. We refer to very low certainty evidence as “uncertain effect.”

RESULTS

The search yielded 4581 records, of which we screened 3822 after duplicate removal (Figure 1). Of these, 3768 records were excluded after screening titles and abstracts, primarily because they were not reports of interventional studies ($n = 2017$) or they did not concern no-shows ($n = 1579$). We included 11 reports on 9 studies, 8 of which were completed and 1 was an incomplete study, suspended due to COVID-19 (NCT04376736). The suspended study reported no outcome data and therefore was not included in data extraction. One study did not report attendance outcomes but was included in the review because the main outcome (idle magnetic resonance imaging [MRI] scanner time) was relevant to the research question.³⁷

All 8 studies were conducted in high-income countries ($n = 5$, 63% in the United States and 1 study each in Italy, Singapore, and Spain), all but 1 study was randomized and none reported industry funding. Two studies were conducted in dermatology,^{38,39} and 2 in outpatient primary care.^{20,40} Other settings included a diagnostic MRI clinic, endoscopy, oncology, mental health, and pneumolgy.^{20,37,39,41–43}

Four intervention types were identified from the initial examination and categorization of the data. Three studies assessed overbooking,^{37,38,41} 3 studies assessed phone call reminders,^{39,40,42} 1 study assessed text message reminders,²⁰ and 1 study assessed patient navigators.⁴³ In all studies, the output of the predictive

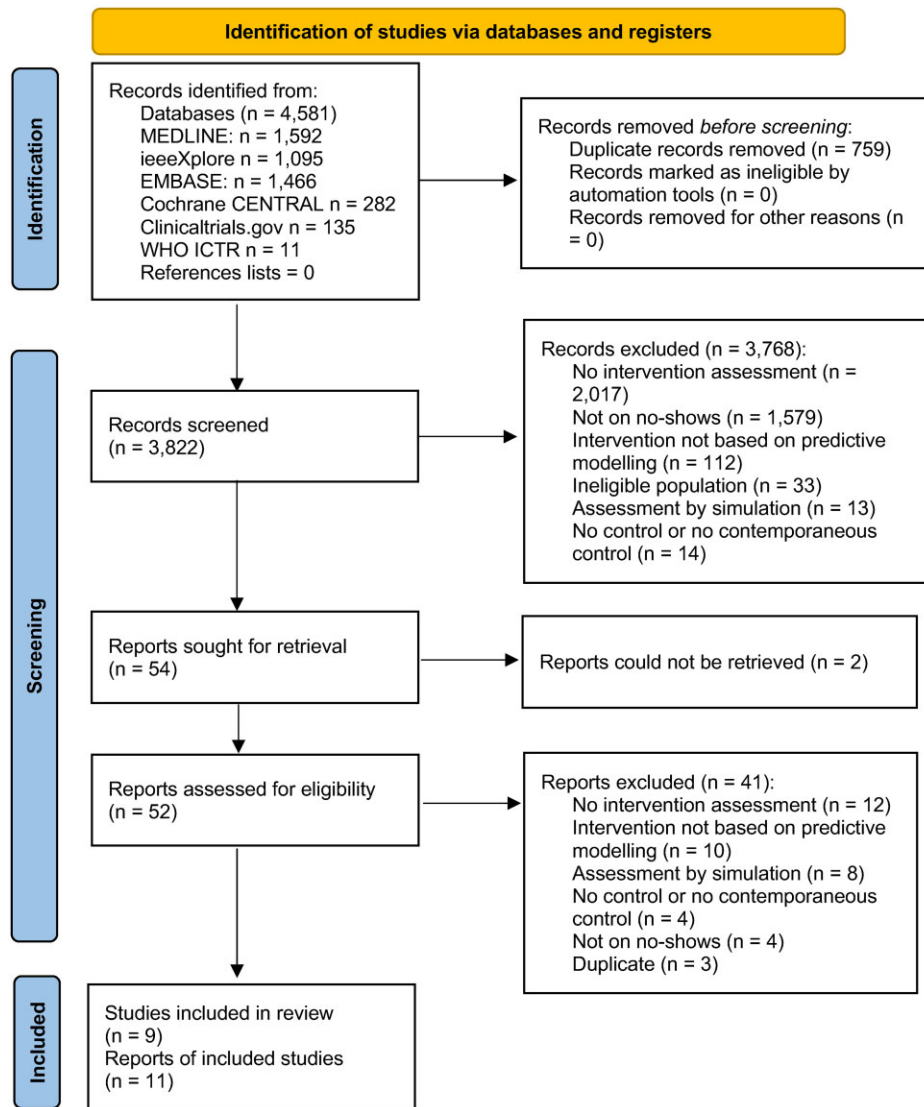


Figure 1. PRISMA flow chart. Overall, 4581 records were identified and 3822 were screened after duplicate removal. Eight completed studies and 1 registered, suspended study were eligible for inclusion in the review.

model was used to select intervention recipients at high risk of a no-show. The median follow-up was 22 weeks (interquartile range [IQR] 11, 25 weeks) and the median sample size was 3851 appointments (IQR 1108, 4425 appointments). The comparator was usual appointment scheduling practice in all studies, but the definition of usual practice varied among studies. A detailed description of the studies is presented in [Table 1](#). The characteristics of the predictive models are presented in [Supplementary Table S1](#).

Prediction model plus phone call reminders versus usual scheduling practice

In 3 RCTs (analyzing a total of 4959 appointments), patients identified by a predictive model to be at high risk of no-show received phone call reminders.^{39,40,42} The median no-show RR from these 3 RCTs was 0.61 (IQR 0.49, 0.68, min 0.49, max 0.75). Considering the GRADE assessment, there is moderate certainty evidence that predictive model-based phone call reminders probably reduce no-shows ([Table 2](#)). Uncertainty was due to the risk of bias ([Figure 2](#)). Two of the 3 RCTs (analyzing 3851 appointments) provided very

low certainty evidence on the effect of predictive model-based phone call reminders on cancellations and reschedules, due to the risk of bias, indirectness, and imprecision ([Supplementary Table S2](#)).^{40,42} One of the 3 RCTs (analyzing 3851 appointments) provided moderate certainty evidence due to the risk of bias that predictive model-based phone call reminders probably do not increase attendance ([Supplementary Table S2](#)).⁴⁰

Costs, acceptability, and equity

One of the 3 RCTs reported an effect of predictive model-based phone call reminders on the mean relative value units per patient (ie, a measure of value for physician services used in the United States, absolute difference 0.13, 95% CI -0.02 to 0.28).⁴⁰ In one of the other RCTs, the authors conducted postintervention debriefing with 8 physicians and managers and found that they considered the intervention successful, but that there were issues with the workload resulting from achieving fewer no-shows and the workload associated with implementing the intervention.³⁹ No information was reported on equity.

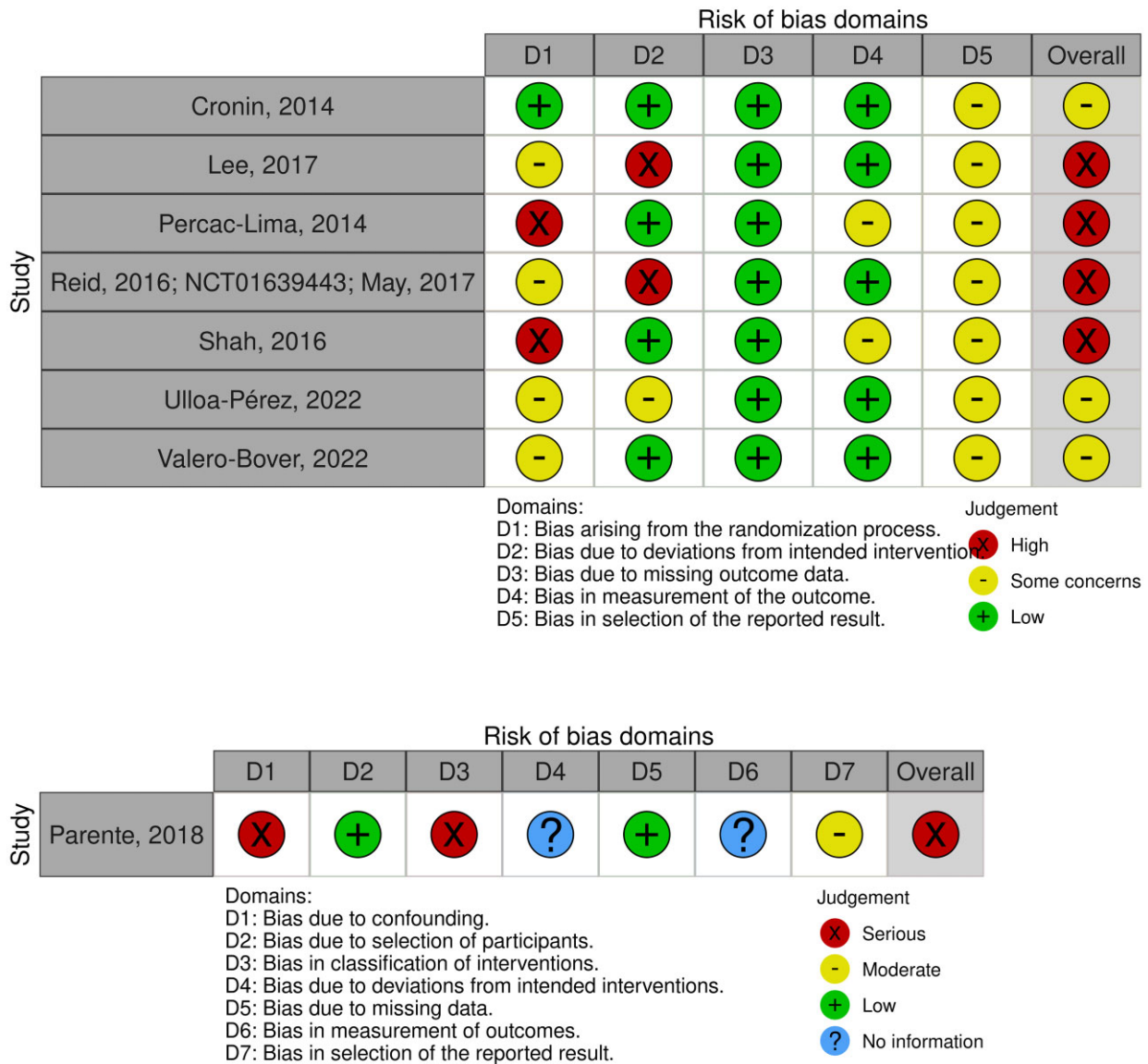


Figure 2. Risk of bias of the included studies. The figure presents the risk of bias in the included studies, evaluated using the Cochrane Risk of Bias tool (ROB 2) for randomized controlled trials (top panel) and the Risk Of Bias In Nonrandomized Studies of Interventions (ROBINS-I) for nonrandomized controlled trials (bottom panel). Four (57%) randomized controlled trials were at high risk of bias and the nonrandomized controlled trial was at serious risk of bias. There were some concerns for the remaining randomized controlled trials.

Prediction model plus text message reminders versus usual scheduling practice

In 1 RCT (analyzing a total of 158 669 appointments) patients identified by a predictive model to be at high risk of no-show received text message reminders.²⁰ No-show RR was reported separately for primary care and mental health appointments (median RR 0.91, interquartile range 0.90, 0.92, min 0.89, max 0.93) (Table 2). There is high certainty evidence that predictive model-based text message reminders reduce no-shows. This RCT also provided low certainty evidence due to imprecision that predictive model-based text message reminders may increase cancellations (median RR 0.98, interquartile range 0.96–1.00, min 0.94, max 1.02) (Supplementary

Table S2). In this study, the outcome was defined as same-day cancellations.

Costs, acceptability, and equity

A sensitivity analysis found no evidence of heterogeneous intervention effect on no-show rates by age, sex, race, or amount of co-pay.²⁰ No information was reported on costs and acceptability.

Prediction model plus patient navigator versus usual scheduling practice

In 1 RCT (analyzing a total of 4425 appointments) patients identified by a predictive model to be at high risk of no-show received

Table 1. Characteristics of the included studies

Study	Design	Participants	Comparator	Predictive model-based intervention	Follow-up
Phone call reminders Lee et al ⁴²	RCT	800 appointments in 1 women's and children's hospital in Singapore; unreported number of patients	Usual practice (no intervention)	The predictive model was used to generate daily reports. Appointments were color-coded based on no-show probability, presented alongside patient contact information and appointment information. Staff contacted the 50 patients at highest no-show risk daily, 2 working days before their appointments, using prespecified call verbiage to confirm attendance, cancel, or reschedule the appointment (up to 3 contact attempts).	8 days
Shah et al ⁴⁰	RCT	2247 primary care patients in 1 hospital in the United States; unreported number of appointments	Usual practice (reminders)	Patients classified as no-shows by the predictive model were queued on a dedicated module in TopCare, an online, EHR-interoperable platform, 7 days before their appointment. The platform presented their contact information (name, phone number, appointment date and time, physician, and emergency contact) and the outcome of the reminder call. A reminder phone call was made to patients at ≥ 0.15 no-show risk, by a trained patient coordinator, using behavioral techniques to increase attendance.	6 months
Valero-Bover et al ³⁹	RCT	805 dermatology and 303 pneumonology patients in 1 hospital in Spain; unreported number of appointments	Usual practice (no intervention)	A reminder phone call was made 1 week before the appointment to patients at high risk of no-show according to the predictive model. Up to 3 contact attempts were made. Patients were encouraged to attend their appointment or cancel it.	2 months
Text message reminders Ulloa-Perez et al ²⁰	RCT	125 076 primary care appointments and 33 593 mental health appointments in 1 hospital in the United States; unreported number of patients	Usual practice (reminders)	No-show predictions were generated every night for next week's appointments, within Epic. An additional text message reminder (ie, 2 reminders in the intervention group vs 1 reminder in the control group) was sent 3 days before the appointment to patients at >0.51 risk of no-show for primary care and >0.21 risk of no-show for mental health. Patients were asked to confirm the appointment or cancel by phone or online.	7 months
Patient navigator Percac-Lima et al ⁴³	RCT	4425 oncology appointments in 1 hospital in the United States; unreported number of patients	Usual practice (reminders)	The predictive model was used to generate reports at 7 and 1 days preappointment, listing no-show risk and patient information for all appointments (ie, EHR number, name, sex, age, date, time and reason for appointment, physician and contact information, recent hospitalization, language, clinic, location, and the outcome of the navigation phone call made to patients). A trained patient navigator, fluent in English and in Spanish, used the report to call the 20% of patients at highest no-show risk per day, at 7 days and 1 day before the appointment. The patient navigator confirmed the appointment and offered support as needed, including discussing components of the visit, answering questions, addressing barriers to attendance, and facilitating further patient-staff communication (up to 2 calls per patient, calls lasted 2–10 min).	5 months
Overbooking Cronin and Kimball ³⁸	RCT	Dermatology patients in 1 hospital in the United States; unreported sample size	Usual practice (overbooking based on historical booking maximums)	The predictive model was used to generate 2 reports within the Smart Booking system. The first report was used by staff in charge of appointment scheduling, to manage overbooking for the next 2–60 days, and the second report was generated daily	4 months

(continued)

Table 1. continued

Study	Design	Participants	Comparator	Predictive model-based intervention	Follow-up
Reid et al ⁴¹ May et al ⁴⁴	RCT	2446 endoscopy patients in 1 hospital in the United States, unreported number of appointments	Usual practice (reminders)	and was used to manage overbooking the following day. Both reports identified appointments to overbook and suggested which appointment types should be booked in these slots. Physician preferences for overbooking were taken into account. The predictive model was used to identify appointments with no-show risk >0.45 scheduled in the following 2 weeks. Staff did not overbook the appointment identified by the model. Instead, researchers actively recruited patients seeking care into “fast track” appointments, that is, appointments without a strictly specified time, in the half-day morning or afternoon slot of the likely no-show. “Fast track” appointments occurred within 2 weeks instead of the usual wait time of >30 days. Patients who opted in received a phone call to finalize the booking.	9 months
Parente et al ³⁷	Non-RCT	29 320 appointments in 1 magnetic resonance clinic in Italy; unreported number of patients	Usual practice (reminders)	Limited information is provided about the overbooking process. Appointment no-show probabilities, produced using the predictive model, and average expected appointment duration were used to estimate the number of minutes available for overbooking per day. When the available overbooking minutes were equal to the time needed for an examination, the appointment with the highest no-show probability of the day was overbooked. This occurred daily, for appointments scheduled the day after the next. The created appointments were filled on a first-come-first-served basis.	6 months

Abbreviations: EHR: electronic health record; RCT: randomized controlled trial.

phone calls from a patient navigator.⁴³ The RCT provides moderate certainty evidence due to the risk of bias that predictive model-based patient navigator calls probably reduce no-shows (RR 0.55, 95% CI 0.46–0.67, Table 2) and increase cancellations (RR 1.16, 95% CI 1.04–1.29, Supplementary Table S2).

Costs, acceptability, and equity

The average net income associated with this intervention was \$5000 per month.⁴³ In a subgroup analysis (unreported numeric data, odds ratios of appointment attendance for race, language, gender, age, and insurance subgroups presented in figures), the effect of the patient navigator intervention was significant for anglophone patients but not for other language groups, for white and African American patients but not Hispanic and Asian patients, and for Medicare and commercial insurance holders but not for Medicaid holders and self-paying patients. Regarding age, the intervention effect was significant only for patients in the 40–69 age group. No information was reported on acceptability.

Prediction model plus overbooking versus usual scheduling practice

In 2 RCTs and 1 non-RCT (analyzing 31 766 appointments), information on the risk of no-show was used to make overbooking decisions.^{37,38,41} Outcome data could not be summarized, because the 3 studies used different outcomes. Due to the risk of bias, inconsis-

tency, indirectness, and imprecision in the available evidence, there is very low certainty whether there is an effect of predictive model-based overbooking on appointment attendance (Supplementary Table S2).

Costs, acceptability, and equity

Predictive model-based overbooking was associated with a relative increase of 15.4% in hourly revenue in the MRI clinic (absolute difference of 8.14\$, unreported 95% CIs and significance),³⁷ but with higher daily overtime costs in endoscopy (absolute difference of 26.13\$).⁴¹ Regarding acceptability, 1 RCT reported that on intervention days, clinics ran longer by an average 34 min compared to control days (absolute difference 0.47 h [95% CI, 0.06–0.88, $P = .02$]).⁴¹ One non-RCT reported a nonsignificant increase of 6.2 min in patient in-clinic wait time (relative difference 3.66%) and 10 min in staff overtime (4.05%, unreported 95% CIs and significance).³⁷ In 1 RCT, African Americans were twice as likely as whites to take up “fast track” appointments made available by overbooking (adjusted odds ratio 1.99, 95% CI, 1.26–3.17).^{41,44}

DISCUSSION

This rapid systematic review examined 8 RCTs and non-RCTs assessing reminder, patient navigator, and overbooking interventions, all utilizing predictive modeling and aiming to reduce outpatient no-shows. Findings are limited by the small number of studies.

Table 2. Summary of findings

Prediction plus phone reminders compared to usual scheduling for managing appointment attendance

Patient or population: outpatients

Setting: outpatient clinics

Intervention: prediction plus phone reminders

Comparison: usual scheduling

Outcomes	Anticipated absolute effects ^a (95% CI)		Relative effect (95% CI)	No. participants (studies)	Certainty of the evidence (GRADE)
	Risk with usual scheduling	Risk with prediction plus phone reminders			
No-shows Assessed with: hospital records Follow-up: median 2 months	226 per 1000	0 per 1000 (111–169) ^b	RR ranged from 0.49 to 0.75	4959 (3 RCTs) ^b	⊕⊕⊕○ Moderate ^d

Prediction plus text message reminders compared to usual scheduling for managing appointment attendance

Patient or population: outpatients

Setting: outpatient clinics

Intervention: prediction plus text message reminders

Comparison: usual scheduling

Outcomes	Anticipated absolute effects ^a (95% CI)		Relative effect (95% CI)	No. participants (studies)	Certainty of the evidence (GRADE)
	Risk with usual scheduling	Risk with prediction plus text message reminders			
No-shows Assessed with: hospital records Follow-up: 7 months	114 per 1000	0 per 1000 (102–106)	RR ranged from 0.89 to 0.93^c	158669 (1 RCT)	⊕⊕⊕⊕ High

Prediction plus patient navigator compared to usual scheduling for managing appointment attendance

Patient or population: outpatients

Setting: outpatient clinics

Intervention: prediction plus patient navigator

Comparison: usual scheduling

Outcomes	Anticipated absolute effects ^a (95% CI)		Relative effect (95% CI)	No. participants (studies)	Certainty of the evidence (GRADE)
	Risk with usual scheduling	Risk with prediction plus patient navigator			
No-shows Assessed with: hospital records Follow-up: 5 months	131 per 1000	72 per 1000 (60–88)	RR 0.55 (0.46–0.67)	4425 (1 RCT)	⊕⊕⊕○ Moderate ^e

Abbreviations: CI: confidence interval; RCTs: randomized controlled trials; RR: risk ratio.

^aThe risk in the intervention group (and its 95% confidence interval) is based on the assumed risk in the comparison group and the relative effect of the intervention (and its 95% CI).

^bParticipant numbers and risk ratios were unavailable for Lee et al⁴² for all outcomes. Lee et al⁴² reported a statistically significant decrease of –18.7% ($P < .001$) in no-show rate.

^cResults were reported separately for mental health and primary care patients.

^dTwo of 3 studies were at high risk of bias; this included high risk of bias for randomization in the largest study.

^eSingle study at high risk of bias for randomization.

We found that predictive model-based text message reminders were effective at reducing no-shows. Predictive model-based phone call reminders and patient navigator calls were probably effective at reducing no-shows. Finally, it is uncertain whether there was an effect of predictive model-based overbooking on appointment attendance. In addition, we identified evidence gaps in cost-effectiveness, acceptability, and equity, for all interventions.

Regarding secondary outcomes, predictive model-based phone call reminders are probably not effective at increasing attendance, and it is uncertain whether they affect cancellations and reschedules. Predictive model-based text message reminders may increase same-day cancellations, and predictive model-based patient navigator calls probably increase cancellations, probably by making cancellations easier for patients who did not intend to attend their appointments.

Early cancelations, but not last-minute cancelations, could result in more available slots for patients. Overall, the magnitude and direction of intervention effects in the included studies varied, possibly due to heterogeneity in the sample (eg, medical specialty) and outcome definition.

The review findings on reminders align with previous research showing that nontargeted reminders (ie, reminders offered to all patients with scheduled appointments) can reduce no-shows.^{9–13} Our findings should be contextualized by comparison with the literature on the effectiveness of nontargeted interventions. Results from a previous review on the effect of receiving nontargeted reminder phone calls, compared to no reminders, show at least comparable benefits to predictive model-based phone call reminders.¹¹ Results from 1 meta-analysis comparing nontargeted reminder text messages compared to no reminders found that those receiving nontargeted reminder text messages were 25% less likely to no-show, which is a larger benefit than that observed in the included studies of predictive model-based text message reminders.¹⁰ We did not find any studies reporting a head-to-head comparison of targeted versus nontargeted interventions to reduce no-shows. The added value of targeting interventions by using a predictive model to identify appointments at high risk of no-shows is unclear. Relevant to this question is the lack of studies reporting a full cost-effectiveness analysis of predictive model-based interventions, though studies reported limited evidence that patient navigators lead to cost savings, phone call reminders do not affect costs compared to usual scheduling, and overbooking leads to increases in overtime costs and in revenue.

None of the included studies reported a formal acceptability evaluation of the interventions, although some reported stakeholder feedback was reported anecdotally. For example, 1 study reported that staff appreciated the reduction in uncertainty and cognitive effort associated with making overbooking decisions,³⁸ and another study reported that management supported the permanent implementation of the intervention.⁴¹ However, in both cases, data were not collected systematically and the qualitative analysis methodology was unreported, leaving an important evidence gap on whether predictive model-based interventions to reduce no-shows may have undesirable effects (eg, increased patient in-clinic wait time and staff overtime were reported in 1 study).³⁷ Evidence on equity impact was limited, with reminder interventions potentially having a similar effect across demographics, while patient navigators had different effects by language, race, age, and insurance groups. Participants were poorly described in terms of PROGRESS characteristics, which are relevant to health equity (ie, age, gender, place of residence, race/ethnicity, language, occupation, religion, education, and socioeconomic status). For example, only half of the trials reported participants' race/ethnicity. Heterogeneous intervention effects could also be attributed to patient characteristics relevant to equity, but as patient characteristics were poorly reported, this hypothesis could not be explored.

Implications for practice

This review showed that there are many interventions available to care organizations that have access to predictive models of no-shows. Organizations should select interventions that fit their needs and aims. For example, compared with interventions seeking to facilitate access to care (eg, patient navigators), overbooking may not address the impact of no-shows on individual patients' outcomes, and it may increase patients' treatment burden. In 1 included

study, appointments created by overbooking carried a risk of unusually long in-clinic wait times and rescheduling in the event of clinic overload.⁴¹ Organizations should therefore monitor predictive model-based interventions after implementation to ensure that there are no undesirable effects and that benefits are uniformly experienced by all patients.

Implications for research

First, research on cost-effectiveness, staff and patient acceptability, and equity is urgently needed to inform implementation. Such research should seek to be patient-centered. For example, none of the studies reported patient or public involvement, or measured patients' experience, except for in-clinic wait time. Patients who have difficulties managing appointments (eg, because of treatment burden) may have strong views of interventions such as overbooking when these are based on models that include prior no-shows as a predictor. In addition, patient-focused outcomes that can impact clinical outcomes should be measured. For example, an increased risk of discharge could lead to delays in care. Second, except for patient navigators, most of the included studies assessed relatively low-resource interventions. Precision care delivery, based on predictive modeling, could support the delivery of resource-intensive interventions that could not be feasibly delivered to all patients. Future studies could evaluate the effectiveness of such interventions for patient groups who are less likely to benefit from low-resource interventions and develop alternative solutions. Third, outcome types and definitions were heterogeneous and poorly reported. Future studies could facilitate evidence synthesis by reporting no-show data completely (ie, number of no-shows, attended appointments, cancellations, and reschedules per arm). Fourth, the included studies focused on participants classified to be at high risk of no-shows according to predictive models. Future research should study the added value of targeted interventions by comparing targeted versus nontargeted interventions (eg, text message reminders sent to all patients) across all clinic patients. Studies should also directly compare different predictive model-based interventions.

Strengths and limitations

This is the first evidence synthesis of predictive model-based interventions for no-shows. We searched 6 databases, including 2 trial registries to capture unpublished studies, and we performed a complete appraisal of the evidence using the ROB 2, ROBINS-I, and GRADE tools. It identified effective predictive model-based interventions and mapped important evidence gaps. The findings can be used to guide future research and support the current implementation of such predictive models in real-life care settings.

A meta-analysis could not be performed due to the incomplete and unclear reporting of outcome data, and heterogeneity in outcome measures and interventions. Although the range of observed RR is presented, this does not account for differences in the relative sizes of the studies. Second, as this is a rapid review, screening was primarily done by 1 researcher. Although the agreement between reviewers was excellent in the independent screening of 10% of retrieved titles, it is possible that we missed some eligible studies. The findings may not generalize to certain contexts, such as low-income countries and pediatrics. Finally, this review included findings from 8 studies. More high-quality studies are needed on the effectiveness of predictive model-based interventions.

CONCLUSIONS

Despite the limited number of studies, this rapid review found that predictive model-based text message reminders are effective at reducing outpatient no-shows, and phone call reminders and patient navigator calls are probably effective at reducing no-shows. Further research is needed on the effectiveness of predictive model-based overbooking, and on cost-effectiveness, acceptability, and equity, for all reviewed interventions.

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AUTHOR CONTRIBUTIONS

TO conceived the study, collected and analyzed data, and drafted the report. GN provided methodological support in the design of the study, collected data, and revised the report critically for important intellectual content. LM collected data and revised the report critically for important intellectual content. DD, JS, and SNvdV conceived the study and revised the report critically for important intellectual content.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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CONFLICT OF INTEREST STATEMENT

None declared.

DATA AVAILABILITY

The dataset used in the analyses reported in this manuscript will be made available on Open Science Framework upon publication.

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