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Behavioral factors associated with patients' non-attendance: A retrospective study in an outpatient specialty clinic at a women's and children's hospital in Singapore

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ABSTRACT

Background: This study aimed to identify behavioral factors that affect patient attendance in outpatient clinics, especially those related to rescheduling.

Methods: A retrospective study was conducted on 20,386 appointment records for 6,252 patients in an outpatient specialty clinic at a women's and children's hospital in Singapore over 34 months (January 2012–October 2014). Multivariate logistic regression was used to analyze the influence of independent variables on appointment no-shows.

Results: The average no-show rate of the study population was 28.87%. Patient historical behaviors were significantly associated with appointment attendance. In particular, a larger number of previous visits, more historical no-shows, more historical rescheduling events initiated by patients, and more reschedulings initiated by the clinic for the current appointment were positively associated with no-shows. Notably, the number of previous visits was found to exhibit a significantly diminishing marginal effect on no-show rates. Further analyses suggested that for appointments rescheduled by the clinic, subsequent rescheduling by patients was associated with a reduced risk of no-shows.

Conclusions: No-shows were more common in patients who missed more historical appointments or had their appointments rescheduled more frequently. Encouraging patients to reschedule their own appointments could be an effective measure to reduce no-shows. However, the benefit of patient-rescheduling decreased if patients rescheduled appointments repeatedly.

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Introduction

Missed appointments (i.e., no-shows) pose a heavy burden on healthcare systems, reducing revenue, undermining resource utilization, and potentially lowering the quality of patient care [1–3]. Previous studies have indicated that patient no-shows did not occur randomly and identified the need to further analyze relevant risk factors [4]. An increasing number of studies have identified the relationship between no-shows and patient demographics (e.g., age, gender, distance, and race) [5–7]. Other factors influencing no-shows included appointment characteristics (e.g., appointment date) [8] and payment forms [5]. In particular, many studies found connections between the historical behavior of patients and attendance. For example, patients who had missed previous appointments were more likely to miss their current appointments [9]. Interestingly, larger numbers of previously scheduled visits were associated with higher or lower no-show rates [3,10], and lastly, a comprehensive literature review examining no-show risk factors was provided by Dantas et al. [4].

To combat no-shows, managers either intervene with patients to improve their attendance or rely on prediction models to estimate patients' no-show probabilities so that mitigation strategies can be prepared in advance. The latter usually involves using data to predict potential no-shows and practicing overbooking to compensate for the underutilization caused by possible no-shows [11]. Since overbooking may lead to physicians/nurses working overtime and prolong patient waiting time, we mainly discuss the interventions that aim at reducing no-shows from the root of the problem. Many types of interventions have been used to discourage no-shows. These interventions included but were not limited to incentives [12], message reminders [13], staff call reminders [14], patient education and navigation [15], providing effective patient communication [16], implementing telehealth in place of the in-person visit [17], and rescheduling

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[8]. These interventions proved to reduce no-shows significantly. Overall, offering patients options to reschedule their appointments is much less costly than the other types of interventions. However, in practice, unexpected events involving clinics, physicians, or patients still occur, and all of these can result in either clinics or patients rescheduling some appointments. Liu et al. demonstrated that patients were less likely to no-show when their appointments were rescheduled by themselves but more likely to no-show when the clinic rescheduled their appointments [8]. However, some questions regarding rescheduling behavior remain unanswered. In some healthcare systems, patients are provided with multiple opportunities to change appointments [18]. So in such systems, it would be beneficial to know if patients' no-show probability decreases equally every time they reschedule or if the reduction of the probability of no-shows diminishes as patients continue to reschedule their own appointments. Given that patients would be less likely to show up if their appointments were rescheduled by the clinic rather than themselves, what the clinic should do to prevent patients from missing appointments is the pertinent question. This study aimed to answer these questions by conducting a retrospective analysis of an operational dataset extracted from an outpatient clinic in Singapore. We expect the results to provide healthcare providers and policymakers with useful insights into managing outpatient appointments.

Literature review

Previous literature has long discussed risk factors associated with patients' no-show behavior. Generally, these factors could be categorized into five groups: demographics, historical behavior, disease information, appointment characteristics, and environmental factors. Among these, patient demographics and appointment characteristics were mostly studied. These demographic factors usually included sex, age, socioeconomic status, birthplace, insurance type, ethnicity, distance from clinics, etc. Many studies observed a consistent association in which higher no-show risk correlated with factors including a younger age [19–24], being male [24], specific language spoken at home [25], having a specific birthplace [25], living in a shelter or being homeless [26], having a lower median income [27], living further from the clinic [27], and having specific insurance types [21,22]. Notably, children were characterized by different no-show patterns. For example, among children, younger patients were associated with fewer missed appointments [20,28]. Appointment characteristics, such as visits on Mondays [19,28] and Fridays [28], and visits in the morning [28], were also found to be associated with an increased no-show risk. Disease information, such as having a commodity [26], or having a history of previous stroke [29], was also associated with a higher no-show risk. In addition, studies considering environmental factors found that no-show rates were associated with snowfall [27] and extreme temperatures [22].

Exploring no-show patterns through analyses of patients' historical attendance and scheduling behavior has increased in popularity in recent years. The risk factors considered in this category included the number of previous visits [19,20,30,31], the number of previous no-shows and cancellations [11,20,30–32], the number of scheduled appointments [29], and appointment confirmation status [24]. Ahmadi et al. found that patients were more likely to show up when their appointments were confirmed [24]. Other studies observed that higher no-show risk was associated with more historical no-shows and cancellations [11,20,30–32]. Regarding the number of previous visits, mixed results were reported in the literature, with the higher no-show risk being associated with high [29] and low [19,20,30] numbers of previous visits. Notably, Soh et al. observed that compared to patients who previously scheduled and attended visits, those who never scheduled appointments (i.e., new to the clinic) were less likely to no-show [31]. Negrete-Najar et al. found that a larger number of scheduled appointments during the year was associated with increased no-show risk [29]. Norris et al. summarized related literature regarding the impact of historical patient behavior on no-shows [20], and there was little literature studying the specific effect of rescheduling. To the best of our knowledge, Liu et al. were among the first to explore this topic. They exclusively considered patients whose appointments were rescheduled fewer than once and found that patient no-show risk decreased when their appointments were rescheduled by patients but increased when appointments were rescheduled by the clinic [8]. However, the effect of patients' *historical rescheduling behavior* remained unknown. In practice, some healthcare systems provide patients with multiple opportunities to reschedule their appointments [18], yet it remains unclear how multiple rescheduling opportunities could reduce or otherwise affect the no-show risk. This study aimed to fill this gap in the literature by providing a more nuanced analysis of the impact of rescheduling on no-show rates.

Data and methods

A complete and de-identified dataset was collected from a specialty clinic in a women's and children's hospital in Singapore. The dataset contained 6,252 patients, with 20,386 appointments over 34 months (January 2012–October 2014). Data exclusion criteria were not applied in this study, and three possible

endpoints for an appointment were used: show-up (i.e., kept appointment), non-attendance without cancellation, and cancellation. In the main analysis, non-attendance without cancellation and cancellation were combined into a single outcome referred to as the 'no-show'. As a robustness check, cancellation records were removed, and non-attendance without cancellation was treated as the only no-show outcome.

Multivariate logistic regression was used to analyze the effects of various factors on patient no-show rate [33]. The area under the receiver operating characteristic curve (AUC) was used to assess the discriminative power of the models. In a multivariate logistic regression model, behavioral variables of interest (e.g., patients' rescheduling behavior and historical behavior) and other control variables, such as demographics, were simultaneously included to predict the final status of an appointment, i.e. no-show or kept the appointment. The risk factors included in the regression models were (1) demographic and social-economic information, such as age, race, nationality, residential address, and subsidy; (2) historical behavior, including the number of prior visits, number of previous no-shows, *number of previous patient-initiated reschedulings prior to the current appointment*, and *number of previous clinic-initiated reschedulings prior to the current appointment episode*; (3) current appointment information, including appointment time, appointment date, total waiting time (i.e., the time elapsed between appointment booking date and appointment date), number of patient-initiated reschedulings during the current appointment episode, and number of clinic-initiated reschedulings during the current appointment episode. Specifically, *the number of previous patient-initiated reschedulings prior to the current appointment*, and *the number of previous clinic-initiated reschedulings prior to the current appointment episode*, which capture patients' historical rescheduling behavior, are new factors yet to be considered in the previous studies.

Before incorporating these independent variables into the regression model, we assessed collinearity between variables by correlation matrix and generalized variance inflation factors (GVIF) statistics; typical cut-off values, an absolute value of correlation coefficient >0.8 and a GVIF >5, were used to signal significant multicollinearity [34]. No significant multicollinearity was observed; therefore, all independent variables were eligible for analysis.

Quadratic terms of several key variables were included to investigate the nonlinear effects. These included the number of previous visits, number of previous no-shows, number of previous patient-initiated reschedulings, number of previous clinic-initiated reschedulings, number of patient-initiated reschedulings for the current appointment, and number of clinic-initiated reschedulings for the current appointment. The quadratic terms are expressed as 'original variable^2': for example, the quadratic term of 'previous visits' is 'previous visits^2', and the quadratic term of 'previous no-shows' is 'previous no-shows^2'.

In addition to the full sample analysis, the compensation effect of patient-initiated rescheduling was also analyzed. A subsample containing patients who experienced clinic-initiated rescheduling exactly once was used for the latter analysis. The subsample consisted of 1,504 patients with 1,796 appointment records. For this subsample analysis, patient-initiated rescheduling after clinic-initiated rescheduling is a new variable that has not yet been explored in previous studies. It is noteworthy that all the analyses were performed at the appointment level instead of at the patient level.

Additional robustness tests and analyses were carried out by considering models with different combinations of variables and alternative definitions for categorical variables. The R language and the integrated development environment RStudio were used for all the analyses.

Results

Table 1(a and b) summarize the descriptive statistics of the full sample. Table 1(a) reports χ^2 test results for categorical variables, and Table 1(b) reports t-test results for mean values of the numeric variables. For simplicity, we omit 'No. of (i.e. number of)' when presenting names of the variables hereafter. For example, we write 'No. of previous visits' as 'previous visits' by omitting 'No. of'.

Full sample analysis

Table 2 summarizes the regression results for the full sample. The column titled '*Full Model (Main Analysis)*' summarizes our main analysis. The effects of independent variables are represented by odds ratios. Odds ratios (OR) higher than one indicated a higher probability of no-shows with an increase of a given independent variable, assuming all other independent variables were fixed. Patient historical behavior was found to be significantly associated with patient no-show rate. In particular, a larger number of previous visits (previous visits, OR = 2.43, $P < 0.01$), a larger number of previous no-shows (previous no-shows, OR = 1.31, $P < 0.01$), and a larger number of previous patient-initiated reschedulings (previous patient-rescheduling, OR = 1.06, $P < 0.01$) were positively correlated to no-show probabilities in the current appointments.

Features of current appointments were also found to have influenced patients' no-shows. In particular, greater exposure to clinic-initiated reschedulings (current clinic-rescheduling, OR = 1.23, $p = 0.01$), Thursday appointments (OR = 1.25, $P < 0.01$), and longer total waiting

Table 1a. Patient characteristics [categorical variables].

Independent variables		Total (*N*)	No-show (*N*)	No-show rate (%)	Unadjusted OR	χ^2	*P*-value
Age	(15, 30]	5,799	1,886	32.52%	1.00	138.63	<0.01
	(30, 45]	9,236	2,775	30.05%	0.89		
	(45, 60]	4,681	1,082	23.11%	0.62		
	(60,]	670	142	21.19%	0.56		
Subsidy	Subsidized	9,886	2,477	25.06%	1.00	135.48	<0.01
	Non-subsidized	10,500	3,408	32.46%	1.44		
Race	Chinese	12,796	3,475	27.16%	1.00	51.34	<0.01
	Malay	2,765	849	30.71%	1.19		
	Indian	2,465	795	32.25%	1.28		
	Others	2,360	766	32.46%	1.29		
Nationality	SGP	14,934	4,135	27.69%	1.00	37.61	<0.01
	Non-SGP	5,452	1,750	32.10%	1.23		
Day of week	Monday	6,551	1,912	29.19%	1.00	33.55	<0.01
	Tuesday	2,950	753	25.53%	0.83		
	Wednesday	4,570	1,374	30.07%	1.04		
	Thursday	2,296	735	32.01%	1.14		
	Friday	4,019	1,111	27.64%	0.93		
Period of day	Morning	11,070	3,203	28.93%	1.00	0.04	0.83
	Afternoon	9,316	2,682	28.79%	0.99		

Notes: OR, odds ratio; SGP, Singapore citizen.

Table 1b. Patient characteristics [Numeric variables].

Independent variables	Total (20,386)	No-show (5,885)	Show-up (14,501)	*t*	*P*-value
Distance, mean (SD)	9.83 (4.29)	9.77 (4.37)	9.85 (4.26)	−1.07	0.28
Previous visits, mean (SD)	1.34 (1.40)	1.71 (1.27)	1.19 (1.42)	25.51	<0.01
Previous no-shows, mean (SD)	0.37 (0.93)	0.56 (1.35)	0.29 (0.68)	14.71	<0.01
Previous patient-rescheduling, mean (SD)	0.59 (0.85)	0.82 (2.14)	0.50 (1.71)	10.22	<0.01
Previous clinic-rescheduling, mean (SD)	0.49 (1.76)	0.63 (1.95)	0.43 (1.67)	6.84	<0.01
Current patient-rescheduling, mean (SD)	0.14 (0.41)	0.12 (0.39)	0.15 (0.42)	−4.66	<0.01
Current clinic-rescheduling, mean (SD)	0.14 (0.41)	0.20 (0.48)	0.11 (0.38)	11.93	<0.01
Total waiting time, mean (SD)	10.37 (13.36)	15.28 (16.07)	8.38 (11.51)	29.96	<0.01

Notes: Previous visits, the number of times a patient visited the clinic previously; Previous no-shows, the number of times a patient no-showed in the clinic previously; Previous patient-rescheduling, the number of times a patient ever rescheduled his/her appointments previously by himself/herself; Previous clinic-rescheduling, the number of times a patient's appointments were rescheduled previously by the clinic; Current patient-rescheduling, the number of times a patient rescheduled his/her current appointment by himself/herself; Current clinic-rescheduling, the number of times a patient's current appointment was rescheduled by the clinic.

times (OR = 1.03, $P < 0.01$) were positively correlated to no-shows. In contrast, a larger number of previous clinic-initiated reschedulings (previous clinic-rescheduling, OR = 0.94, $P < 0.01$) and a larger number of patient-initiated reschedulings for current appointments (current patient-rescheduling, OR = 0.47, $P < 0.001$) were negatively correlated with no-show rate.

Notably, some quadratic terms were statistically significant. A quadratic term of an independent variable was used to test whether the effect of the variable was increasing or decreasing. In this analysis, we observed that the quadratic term of current patient-rescheduling was significantly larger than one (current patient-rescheduling^2, OR = 1.23, $P < 0.01$), which meant that the benefits (i.e., reducing no-show risk) of patient-initiated reschedulings tended to decrease as patients rescheduled more frequently. However, the negative effects (i.e. increasing no-show risk) of clinic-initiated reschedulings did not significantly diminish as the clinic rescheduled a patient's appointment multiple times (current clinic-rescheduling^2, OR = 0.95, $p = 0.15$).

In addition, it was also found that including the historical behavior variables could significantly increase the prediction accuracy of the regression model. The AUC of this study's model was 0.73 (Table 2), compared to 0.70 for the model without considering patient historical behavior variables (Table S1 in Supplementary Material).

Subsample analysis

Regression results for the subsample analysis are presented in Table 3. The column titled '*Full Model (Main Analysis)*' summarizes our main analysis for the subsample. It was observed that compared to those who were only rescheduled once by the clinic, patients who rescheduled their appointments by themselves after being rescheduled by the clinic had lower no-show rates (latest rescheduling = by patient, OR = 0.43, $P < 0.01$). The number of previous visits (OR = 1.49, $P < 0.01$) was significantly associated with increased no-shows, and its negative effects tended to decrease, consistent with the full sample analysis.

Separate models and alternative definitions

Two separate models with *only demographic* variables and *only behavioral* factors were analyzed. The results are presented in the first two columns in Tables 2 and 3. The models with only demographic variables (the column '*Demographics Only*') were seen to have

much lower discriminative power than the model with only behavioral factors (the column '*Behavioral Only*'); AUC = 0.57 vs. 0.72 in the full sample analysis and AUC = 0.59 vs. 0.64 in the subsample analysis. This observation confirmed the importance of including behavioral factors in analyzing patient no-shows. Further analysis was conducted of a model using fewer categories for the categorical variables (Tables S2 and S3 in Supplementary Material). These results were consistent, i.e., all the behavioral variables of interest remained statistically significant, and the estimated ORs were very similar.

Discussion

Medical appointment no-shows have been a notorious problem faced by many outpatient clinics that require patients to make appointments in advance. Thus it is important to understand patient behavior and their reaction to uncertain events during the appointment process. The analyses of this study confirmed that patients with a history of more frequent no-shows missed more appointments, which was consistent with previous studies [4,9,20]. Furthermore, several new behavioral factors significantly associated with no-shows have been identified. In particular, *the number of previous patient-initiated reschedulings was positively correlated with an increased risk of no-shows*. A larger number of previous patient-initiated reschedulings indicated that a patient's personal schedule frequently fluctuated, and consequently, the patient missed more appointments. On the other hand, a larger number of rescheduling requests might also reveal that the patient perceived a lower value for a particular appointment, which resulted in more non-attendance.

Table 2. Multivariate analysis of the risk factors for patient no-shows (full sample).

	Demographics only			Behavioral only			Full model (main analysis)		
Variables	OR	95% CI	*P*-value	OR	95% CI	*P*-value	OR	95% CI	*P*-value
Age									
Base: (15, 30]	1.00	–	–				1.00	–	–
(30, 45]	0.87	0.81–0.93	<0.01				0.81	0.75–0.88	<0.01
(45, 60]	0.66	0.61–0.72	<0.01				0.58	0.53–0.64	<0.01
(60,]	0.62	0.51–0.76	<0.01				0.62	0.50–0.77	<0.01
Subsidy									
Base: Sub	1.00	–	–				1.00	–	–
Non-sub	1.37	1.28–1.46	<0.01				1.40	1.30–1.50	<0.01
Race									
Base: Chinese	1.00	–	–				1.00	–	–
Malay	1.14	1.04–1.25	0.01				1.24	1.12–1.37	<0.01
Indian	1.17	1.06–1.29	<0.01				1.27	1.15–1.40	<0.01
Others	1.08	0.97–1.20	0.17				1.08	0.97–1.21	0.17
Nationality									
Base: SGP	1.00	–	–				1.00	–	–
Non-SGP	1.01	0.93–1.10	0.80				1.07	0.98–1.17	0.13
Distance	1.00	0.99–1.00	0.53	1.00	0.99–1.00	0.26	1.00	0.99–1.00	0.26
Previous visits				2.28	2.13–2.44	<0.01	2.43	2.27–2.60	<0.01
Previous visits^2				0.87	0.86–0.88	<0.01	0.86	0.85–0.88	<0.01
Previous no-shows				1.34	1.26–1.42	<0.01	1.31	1.23–1.40	<0.01
Previous no-shows^2				1.00	0.99–1.01	0.76	1.00	0.99–1.02	0.86
Previous patient-rescheduling				1.05	1.01–1.09	0.01	1.06	1.02–1.10	<0.01
Previous patient-rescheduling^2				1.00	1.00–1.00	0.12	1.00	1.00–1.00	0.08
Previous clinic-rescheduling				0.95	0.92–0.98	<0.01	0.94	0.91–0.97	<0.01
Previous clinic-rescheduling^2				1.00	1.00–1.00	0.04	1.00	1.00–1.00	0.03
Current patient-rescheduling				0.47	0.39–0.56	<0.01	0.47	0.40–0.57	<0.01
Current patient-rescheduling^2				1.22	1.12–1.33	<0.01	1.23	1.12–1.34	<0.01
Current clinic-rescheduling				1.28	1.09–1.49	<0.01	1.23	1.06–1.44	0.01
Current clinic-rescheduling^2				0.94	0.87–1.02	0.12	0.95	0.88–1.02	0.15
Day of Week									
Base: Monday				1.00	–	–	1.00	–	–
Tuesday				0.88	0.78–0.98	0.02	0.92	0.82–1.03	0.16
Wednesday				1.05	0.96–1.14	0.32	1.01	0.92–1.10	0.89
Thursday				1.30	1.16–1.45	<0.01	1.25	1.12–1.40	<0.01
Friday				0.94	0.86–1.04	0.23	0.99	0.90–1.09	0.89
Period of Day									
Base: Morning				1.00	–	–	1.00	–	–
Afternoon				1.02	0.95–1.09	0.67	0.94	0.88–1.01	0.12
Total waiting time				1.03	1.03–1.03	<0.01	1.03	1.03–1.03	<0.01
AUC	0.57			0.72			0.73		
Sample size	20,386			20,386			20,386		

Notes: OR, odds ratio; CI, confidence interval; SGP, Singapore citizen; Previous visits, the number of times a patient visited the clinic previously; Previous visits^2 = Previous visits * Previous visits; previous no-shows, the number of times a patient no-showed in the clinic previously; Previous no-shows^2 = Previous no-shows * Previous no-shows; Previous patient-rescheduling, the number of times a patient ever rescheduled his/her appointments previously by himself/herself; Previous patient-rescheduling^2 = Previous patient-rescheduling * Previous patient-rescheduling; Previous clinic-rescheduling, the number of times a patient's appointments were rescheduled previously by the clinic; Previous clinic-rescheduling^2 = Previous clinic-rescheduling * Previous clinic-rescheduling; Current patient-rescheduling, the number of times a patient rescheduled his/her current appointment by himself/herself; Current patient-rescheduling^2 = Current patient-rescheduling * Current patient-rescheduling; Current clinic-rescheduling, the number of times a patient's current appointment was rescheduled by the clinic; Current clinic-rescheduling^2 = Current clinic-rescheduling * Current clinic-rescheduling; AUC, area under the receiver operating characteristic curve.

Table 3. Multivariate analysis of the risk factors for patient no-show (subsample).

	Demographics only			Behavioral only			Full model (main analysis)		
Variables	OR	95% CI	*P*-value	OR	95% CI	*P*-value	OR	95% CI	*P*-value
Age									
Base: (15, 30]	1.00	–	–				1.00	–	–
(30, 45]	0.71	0.56–0.89	<0.01				0.67	0.53–0.85	<0.01
(45, 60]	0.68	0.52–0.90	0.01				0.62	0.46–0.83	<0.01
(60,]	0.53	0.27–1.05	0.07				0.46	0.23–0.94	0.03
Subsidy									
Base: Sub	1.00	–	–				1.00	–	–
Non-sub	1.57	1.27–1.95	<0.01				1.48	1.17–1.86	<0.01
Race									
Base: Chinese	1.00	–	–				1.00	–	–
Malay	1.25	0.93–1.69	0.14				1.35	0.99–1.85	0.06
Indian	0.86	0.63–1.18	0.34				0.88	0.63–1.21	0.43
Others	1.01	0.73–1.40	0.97				0.99	0.70–1.38	0.94
Nationality									
Base: SGP	1.00	–	–				1.00	–	–
Non-SGP	1.35	1.04–1.74	0.02				1.34	1.03–1.75	0.03
Distance	0.99	0.97–1.01	0.44				0.99	0.96–1.01	0.26
Previous visits				1.35	1.11–1.65	<0.01	1.49	1.21–1.82	<0.01
Previous visits^2				0.93	0.90–0.97	<0.01	0.92	0.89–0.96	<0.01
Previous no-shows				1.18	0.92–1.51	0.20	1.16	0.90–1.48	0.25
Previous no-shows^2				0.99	0.92–1.06	0.77	0.99	0.92–1.06	0.81
Previous patient-rescheduling				1.13	1.00–1.28	0.05	1.14	1.01–1.30	0.04
Previous patient-rescheduling^2				0.99	0.97–1.00	0.09	0.99	0.97–1.00	0.09
Previous clinic-rescheduling				0.92	0.84–1.02	0.10	0.91	0.83–1.01	0.08
Previous clinic-rescheduling^2				1.00	1.00–1.01	0.19	1.00	1.00–1.01	0.19
Latest rescheduling									
Base: CR				1.00	–	–	1.00	–	–
PR				0.40	0.29–0.56	<0.01	0.43	0.31–0.60	<0.01
Day of week									
Base: Monday				1.00	–	–	1.00	–	–
Tuesday				0.92	0.65–1.30	0.62	1.01	0.71–1.45	0.94
Wednesday				1.13	0.88–1.44	0.34	1.11	0.86–1.43	0.45
Thursday				1.50	1.05–2.12	0.02	1.41	0.99–2.01	0.06
Friday				0.97	0.73–1.30	0.84	1.02	0.76–1.37	0.90
Period of day									
Base: Morning				1.00	–	–	1.00	–	–
Afternoon				0.75	0.61–0.91	<0.01	0.72	0.59–0.88	<0.01
Total waiting time				1.01	1.01–1.02	<0.01	1.01	1.01–1.02	<0.01
AUC	0.59			0.64			0.67		
Sample size	1,796			1,796			1,796		

Notes: SGP, Singapore citizen; Previous visits, the number of times a patient visited the clinic previously; Previous visits^2 = Previous visits * Previous visits; Previous no-shows, the number of times a patient no-showed in the clinic previously; Previous no-shows^2 = Previous no-shows * Previous no-shows; Previous patient-rescheduling, the number of times a patient ever rescheduled their appointments previously by themselves; Previous patient-rescheduling^2 = Previous patient-rescheduling * Previous patient-rescheduling; Previous clinic-rescheduling, the number of times a patient's appointments were rescheduled previously by the clinic; Previous clinic-rescheduling^2 = Previous clinic-rescheduling * Previous clinic-rescheduling; Latest rescheduling, the latest rescheduling of the current appointment was CR or PR; CR, clinic-rescheduling; PR, patient-rescheduling; AUC, area under the receiver operating characteristic curve.

Previous studies provided mixed results regarding the effect of the number of previous visits. Some found that the probabilities of missing appointments were reduced with increased numbers of previous visits [3,29], while others observed the opposite effect [10,19,20]. This study found that a higher no-show risk was associated with an increased number of previous visits. Patients may have regarded repeated clinic visits as unnecessary since they already had many historical visits, thus making them more likely to no-show for additional appointments [35].

When a clinic encountered unexpected events (e.g., physician illness and leave) and a patient's appointment could not be kept, the clinic had to reschedule the appointment. This study found that appointments rescheduled by the clinic in this manner were more likely to be missed, consistent with the previous literature [8]. *To mitigate this negative effect, we hypothesized that no-show risk could be reduced by patients rescheduling their own appointments following a clinic-initiated rescheduling. This hypothesis was supported by the analyses of the subsample.* Compared with appointments rescheduled only by clinics, those rescheduled by patients following clinic-rescheduling were associated with reduced no-show risk.

The hospital involved in this study used several information-technology tools, e.g., interactive Short Message Service (SMS) and an online appointment management system, which were implemented to allow patients to manage and reschedule their own appointments. Based on these findings, we further suggest that the clinics actively contact patients when their appointments are rescheduled by the clinics and invite patients to reschedule the affected appointments again. Patient satisfaction will likely increase since patient preferences are valued by the clinics.

This study further observed that the mitigation effect of patient-rescheduling on no-shows would be reduced with the number of patient-rescheduling. In

Singapore, many hospitals put no official limit on the frequency of patient-rescheduling. Excessive patient-rescheduling would likely disrupt the operations but appear to have had little effect toward reducing no-shows. These results showed that it would be wise to limit the number of patient-rescheduling.

In practice, various interventions have been tested and implemented in an attempt to manage no-shows, such as overbooking, patient reminders, patient education, no-show penalties, and incentives. However, overbooking is a compensation strategy to mitigate the negative impact of no-shows rather than an intervention to reduce no-shows. Overbooking may lead to physicians and nurses working overtime and patients' longer in-clinic waiting time. Reminders, especially in the form of staff calls, were proven to reduce no-shows in many contexts, but they were expensive to operationalize [36]. No-show penalties had mixed effects [37,38]. Patient education could significantly reduce no-shows, despite requiring a significant effort from staff [39]. Incentives reduced no-shows but attracted patients who took advantage of these incentives [12]. Therefore, rescheduling stands out as a low-cost and effective intervention among the interventions considered and could be readily adopted in many appointment systems. Previous studies found that no-show risk could be reduced if clinics provided patients with the flexibility to reschedule their own appointments [8]. This study's results were in line with these previous findings but provided more granular insights into how rescheduling could be effectively leveraged to influence and reduce patient no-shows.

This study had several limitations. Firstly, it was performed in a single center (i.e. a single clinic), and there might be differences between the study clinic and other clinics. Nevertheless, the variables used in this study were typically generated by patients' appointment booking process and recorded in appointment management systems, and external validations could be conducted before generalizing the insights to other clinics. Secondly, the retrospective nature of this study limited access to additional variables (e.g. diagnosis, income level) that could influence no-show rates. For the same reason, this dataset did not record detailed reasons for each no-show incidence, so a content analysis on no-shows could not be conducted. This would be an interesting direction for future research if relevant data could be tracked or surveyed by the clinic. Thirdly, this dataset was slightly outdated (January 2012–October 2014). The studied hospital implemented several interventions to reduce no-shows following the study period, which included an advanced short message service that allowed the patient to indicate confirmation or cancellation through a simple reply (e.g. 1 or 2) and a reminder call to patients who were predicted to no-show with high probabilities. Some of the inventions turned out to be too costly with limited effectiveness and hence were ceased by the hospital. These interventions could contaminate the data and confound the estimates of the true effects of historical and current rescheduling behaviors on no-shows. Thus, we chose this study period before the interventions when the appointment system was the same as the one currently used in the hospital. We would like to mention that Singapore has a well-developed healthcare system that is on par with the most advanced systems in other developed countries. The dataset may be old but never obsolete in discovering the patients' behavioral issues and informing the decision-making. More validations using recent data could be conducted to confirm the findings reported in this study. Future research could implement the interventions proposed in our study to evaluate their effectiveness in reducing no-shows.

Conclusions

This study explored the influence of patient behavior on their no-shows. Through a retrospective study, we observed that no-show risk increased when patients had more historical visits and no-shows or when their appointments were rescheduled more frequently. No-show rates for appointments rescheduled by the clinic decreased when the affected patients later rescheduled their own appointments, but such reduction tended to decrease when patients changed their appointments a greater number of times. We suggest that healthcare providers actively engage with patients whose appointments are rescheduled by clinics and provide opportunities for patients to reschedule their own appointments. Meanwhile, we also recommend limiting the number of times a patient could reschedule an appointment to minimize the disruption in the appointment system. Clinical trials are warranted to confirm the effectiveness of the proposed strategies.

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Data availability statement

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is unavailable.

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