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Article

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Managing Waiting Times to Predict No-shows and Cancelations at a Children's Hospital

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Abstract:

Purpose: Since long waits in hospitals have been found to be related to high rates of no-shows and cancelations, managing waiting times should be considered as an important tool that hospitals can use to reduce missed appointments. The aim of this study is to analyze patients' behavior in order to predict no-show and cancelation rates correlated to waiting times.

Design/methodology/approach: This study is based on the data from a US children's hospital, which includes all the appointments registered during one year of observation. We used the call-appointment interval to establish the wait time to get an appointment. Four different types of appointment-keeping behavior and two types of patients were distinguished: arrival, no-show, cancelation with no reschedule, and cancelation with reschedule; and new and established patients.

Findings: Results confirmed a strong impact of long waiting times on patients' appointment-keeping behavior, and the logarithmic regression was found as the best-fit function for the correlation between variables in all cases. The correlation analysis showed that new patients tend to miss appointments more often than established patients when the waiting time increases. It was also found that, depending on the patients' appointment distribution, it might get more complicated for hospitals to reduce missed appointments as the waiting time is reduced.

Originality/value: The methodology applied in our study, which combines the use of regression analysis and patients' appointment distribution analysis, would help health care managers to understand the initial implications of long waiting times and to address improvement related to patient satisfaction and hospital performance.

Keywords: children's hospital, waiting time, cancelations, no-shows

1. Introduction and Literature Review

Since waiting times are directly related to patient satisfaction, one of the most important aspects of a patient's encounter at a hospital is how long they have to wait (Jatulis, Bundek & Legorreta, 1997). Although health care technology and techniques have been improved significantly in the past several years, waiting times are still a concern. Murray showed that in the early 1990's in Kaiser Permanente (California), the largest managed care organization in the United States, the average wait for a general appointment in a primary care department was 55 days (Murray & Tantau, 2000). The physician-staffing firm Merritt Hawkins reported that in 2013 American patients still waited an average of 29 days nationally to see a dermatologist for a skin exam, 32 days for a heart evaluation by a cardiologist in Washington, and up to 66 days to see a family physician in Boston (Merritt Hawkins, 2014). This study analyzed the average wait to get a physician appointment in 15 different metropolitan markets of the US. It included several specialties, and long waits were found for some of them.

Despite these circumstances, waiting list systems have been mostly designed to minimize physicians' idle time. Productivity has been a priority, which may have important impacts on patient waits (Mardiah & Basri, 2013). Nonetheless, it has been proved that these long lead times also have a huge impact on hospitals' performance. Failure to attend medical appointments by patients has been found as a direct consequence of these long waits (Bean & Talaga, 1995). Research by Galucci, Swartz and Hackerman (2005) and research by Green and Savin (2008) showed that the relationship between waiting times and no-shows can be adjusted to a non-linear regression. After an empirical investigation that included factors such as patient's age, financial payer, and patient's prior attendance history; lead time has been recently confirmed to be the largest contributing factor for predicting no-shows and cancelations (Kumar, Norris, Chand, Moskowitz, Shade & Willis, 2014). Research on how to manage waiting lists has mainly focused on mathematical models that help hospitals better manage resources. Queuing theory has been the most common methodology applied, and the possibility of missed appointments has been taken into account in these models (Cayirli, Yang & Quek, 2012; Green, 2010; Green & Yankovic 2011; Liu, 2016).

Missed appointments might cause an inefficient utilization of resources and also reduce the opportunity for other patients to receive timely care. Staff idle time would increase at certain times, although other times extra workload might be needed (Weingarten, Meyer & Schneid, 1997; Macharia, Leon, Rowe, Stephenson & Haynes, 1992). Thus, it is expected that cancelations and no-shows have a significant impact on hospitals' finance and revenue. In 1999, a children's health clinic found a total of 14,000 missed appointments, which represented a loss of over than one million dollars (Pesata, Pallija & Webb, 1999). In 2015, appointments at an academic paediatric neurology clinic were analyzed for one year (Guzek, Gentry & Golomb, 2015). The no-show rate was 26%, which represented more than \$250,000 of yearly revenue. Therefore, it has been proved that hospitals have the capability to measure how much money cancelations and no-shows represent. Research by Wilson-Whiterspoon, Moore and Probst (2001) proposed a detailed analysis on how to measure this financial impact. In that study, 6.5% of the appointments were canceled and 24.4% were a no-show, which represented a daily average loss for the clinic of 14.2% of the estimated revenue. At the same time, according to the American Hospital Association, in 2013, one third of all US hospitals had a negative operating margin (American Hospital Association, 2015). Also, the 2013 Healthcare Provider Innovation Survey, published by AVIA and HIMSS, revealed that 65% of the general hospitals considered cost reduction as one of the top five innovation priorities, being also the top choice for hospitals (Healthcare Information and Management Systems Society, 2013). However, children's hospitals top choice was it to improve knowledge sharing and management; 54% of the children's hospitals considered this choice as one of the top five priorities.

2. Objective

While patients wait longer and longer to get an appointment, hospitals continue to lose money every day because of missed appointments. Consequently, hospitals should see this situation as an improvement opportunity to increase profitability and to retain and acquire patients. The aim of this study is to analyze patients' behavior in order to predict no-show and cancelation rates correlated to waiting times. The analysis is based on a real data from a one-year experience at a US children's hospital. Health care managers might find this study useful for application at their hospitals, as a meaningful relationship exists between turnover and no-show and cancelation rates.

3. Methodology

This study is based on the data from a US children's hospital, which includes all the appointments registered during one year of observation. The hospital has five facilities staffed by over 165 physicians. All types of services were included in the data provided: general practice and medical specialties. In total, 16 types of physician practices were analyzed.

We used the call-appointment interval to establish the wait time to get an appointment. This interval represents the time elapsed between the date that an appointment is registered in the system and the date that the patient visits the hospital, cancels the appointment, or does not show up for the appointment. Four different types of appointment-keeping behavior were distinguished: arrival, no-show, cancelation with no reschedule, and cancelation with reschedule. We analyzed each of the outcomes individually, considering each of them might have a different impact on the hospital's performance. No-shows and cancelations without reschedule affect financially, and cancelations with reschedule have a direct impact on schedule management, and might finally lead to a monetary loss as well, if we cannot fulfill the empty time blocks.

We also distinguished between two types of patients: new patients and established patients. A new patient is defined as a patient who has never had a medical appointment with the hospital, while an established patient has been treated at the hospital before. The main reason for this distinction is that the average income produced by a new patient might be different than the income produced by an established patient. Also, it is important to determine the impact of long waiting lists on new-patient acquisition. The analysis is structured as follows:

- a) Analysis of the current status of each appointment-keeping behavior possible outcome and the average waiting times for each group.
- b) Correlation analysis of waiting times and appointment-keeping behaviors.
- c) Forecast analysis to anticipate the variation of cancelation and no-show rates when changing waiting times.

In order to analyze the data, clustering was necessary to carry out the correlation analysis. Clusters helped reduce the dispersion of patient waiting times to get an appointment, since the call-appointment interval range went from zero (same day appointment) to 394 days.

4. Findings

The preliminary analysis included 22,331 patients and 81,868 appointments in total. New patients made 15,669 appointments and established patients made 66,199. The tables below summarize the results obtained according to the type of outcome: arrivals or missed appointments, which includes no-shows and cancellations with or without reschedule. The tables include the total number of appointments by type, the percent of total appointments, and the average waiting time for each group. The results are shown for new and established patients in Table 1.

Patient Outcome	Total Number of Appointments		Percent of Total Appointments		Average Waiting Time (Days)	
	New	Established	New	Established	New	Established
Arrival	9,184	39,875	58.61%	60.23%	22.50	36.51
No-show	2,194	8,484	14.00%	12.82%	38.29	70.14
Cancellation without Reschedule	1,640	7,120	10.47%	10.71%	41.68	57.80
Cancellation with Reschedule	2,651	10,720	16.92%	16.33%	39.15	72.47
Total	15,669	66,199	100%	100%	29.65	48.47

Table 1. New and established patients' appointments by appointment-keeping behavior.

Source: prepared by the authors based on hospital data

The data showed that, in our hospital, new patients tend to no-show or cancel with rescheduling slightly more than established patients, while established patients tend to cancel without rescheduling more often. In total, new patients missed more appointments (41.39%) than established patients did (39.77%), even if the difference does not seem significant. However, new patients had to wait much less time to get an appointment than established patients did. The average waiting time for new patients was 29.65 days. Established patients had to wait 48.47 days on average. For new-patient arrivals, the average waiting time was only 22.50 days, compared to an average of 39.50 days for new-patient missed appointments, which is almost twice as long. Established patients' appointments performed similar. The waiting time goes from 36.91 days for a patient who arrived at their appointment, up to 67.93 days for an established patient who missed their appointment.

The dispersion analyses for each type of patient and each appointment-keeping behavior are shown in Figure 1. These are scatter graphs for no-shows, cancellations without reschedule, and cancellations with reschedule against waiting time. They include the analyses for both new and established patients.

The logarithmic regression was found as the best-fit function in all cases when plotting no-shows and cancellations with and without reschedule against waiting times. This data is consistent with the analyses

performed by Galucci et al. (2005) and Green and Savin (2008), who both found the same patterns. A weekly cluster was found to be the best-fit cluster for the correlations. In this case, the rates of cancelations and no-shows remain almost constant after week 12. All the R^2 values we obtained for new-patient appointments are over 0.80, which means the relationship is quite significant. For established patients, R^2 values were higher than for new patients, which might be due to a larger sample size. Table 2 includes the equations for the best-fit function and R^2 for each case.

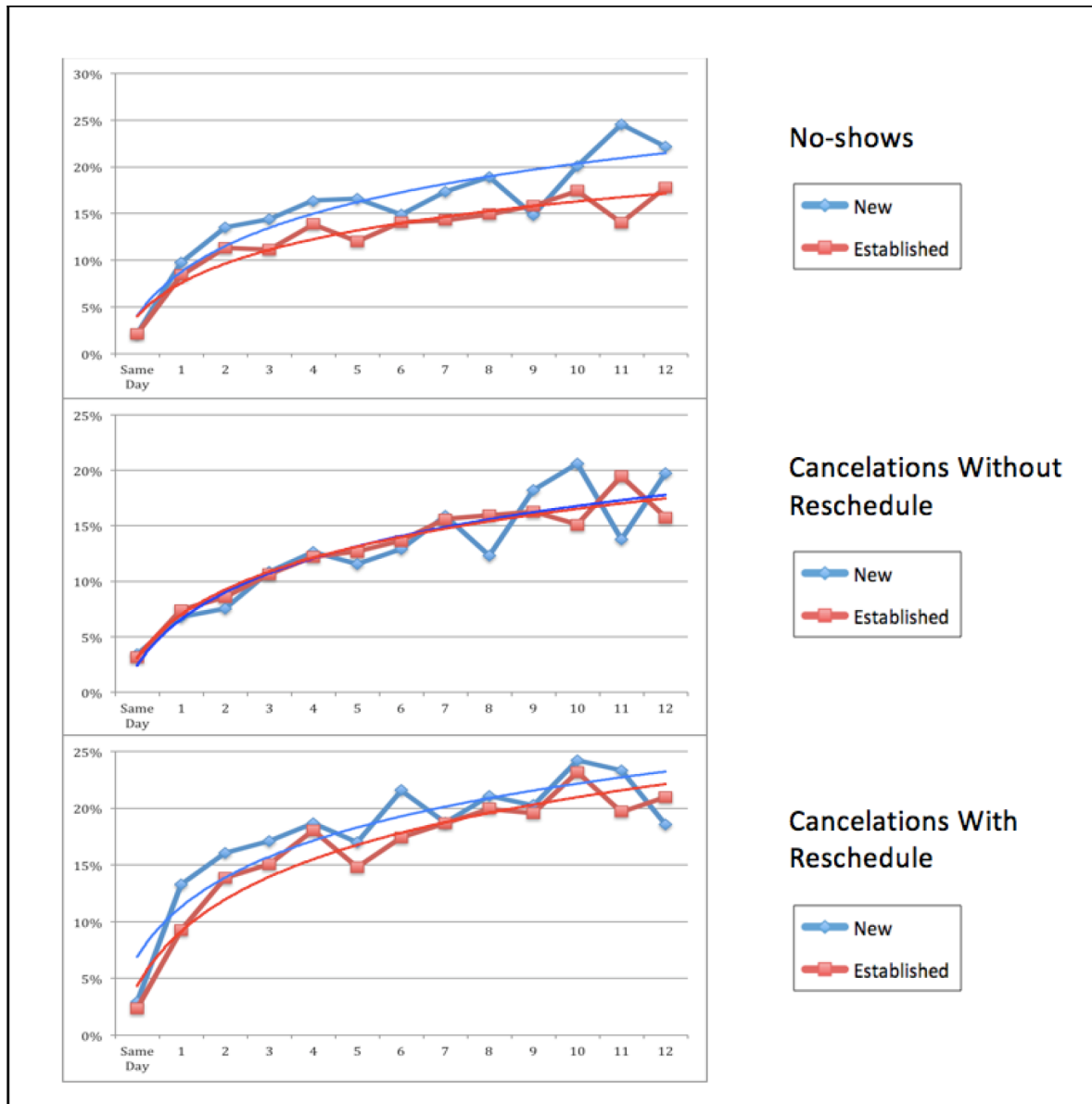


Figure 1. Plot of patient no-show, cancellation without reschedule, and cancellation with reschedule rates by waiting time (in weeks). Source: prepared by the authors based on hospital data

Type of Patient	Patient Outcome	Logarithmic Equation	R ²
New Patients	No-show	$Y=0.0680\ln(x)+0.0402$	0.85502
	Cancellation without Reschedule	$Y=0.0600\ln(x)+0.0283$	0.82339
	Cancellation with Reschedule	$Y=0.0637\ln(x)+0.0685$	0.81365
Established Patients	No-Show	$Y=0.0513\ln(x)+0.0397$	0.90034
	Cancellation without Reschedule	$Y=0.0561\ln(x)+0.0306$	0.94416
	Cancellation with Reschedule	$Y=0.0694\ln(x)+0.0432$	0.91919

Table 2. Characteristics of the best-fit function from Figure 1. Source: prepared by the authors based on hospital data

By combining the distribution graphs (Figures 2 and 3) and the scatter graphs (Figure 1) we were able to predict cancellation and no-show rates of the hospital when changing the waiting times. If the waiting time of every appointment could be reduced by X weeks, every weekly cluster in the distribution graph would also move X weeks through the logarithmic curve, which would therefore reduce the average rate of no-shows and cancellations. The limit for waiting time reduction is the same-day appointment, which represents zero days of wait.

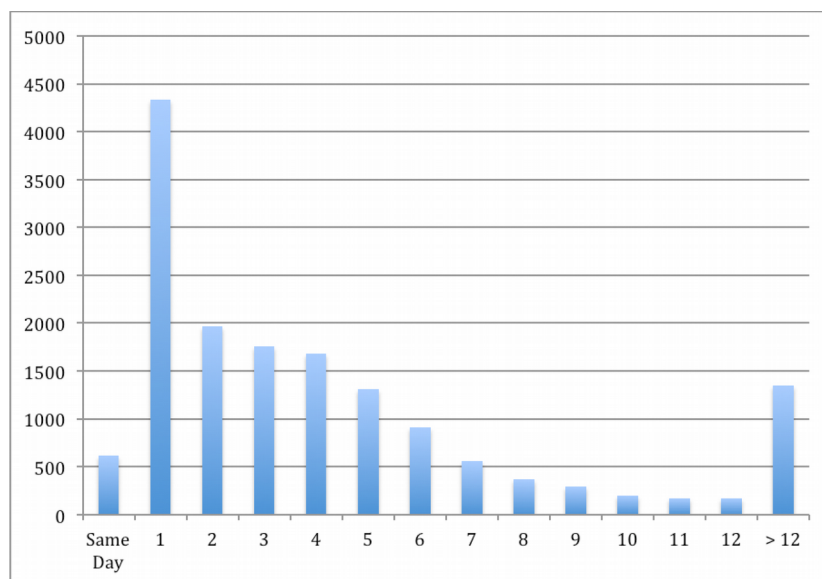


Figure 2. Plot of new patients' appointment distribution by waiting time (in weeks).

Source: prepared by the authors based on hospital data

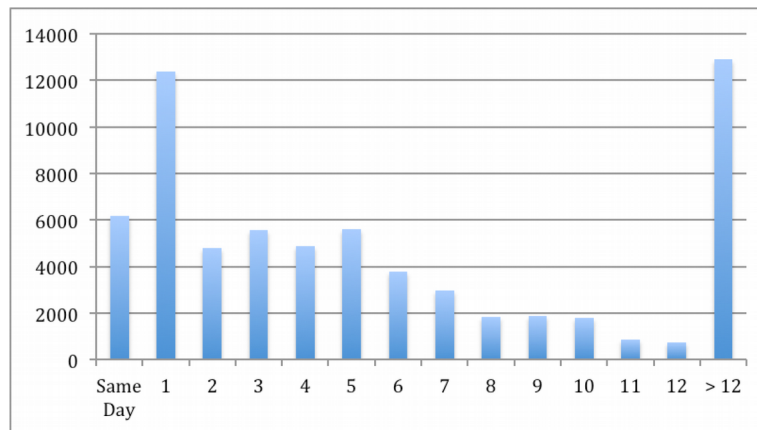


Figure 3. Plot of established patients' appointment distribution by waiting time (in weeks). Source: prepared by the authors based on hospital data

To apply the method, a conservative hypothesis was made: appointments made more than 12 weeks in advance (>12 in Figures 2 and 3) are not subject to the waiting time reduction hypothesis. Consequently, these appointments do not move through the logarithmic curve when the waiting time is reduced for the rest of the appointments in each scenario. Taking into account that missed-appointment rates remain almost constant for long waits, the reduction of missed appointment obtained would be only slightly below the real.

As we can see in Table 3, by reducing the waiting time for each appointment only one week, we could reduce the rate of missed appointments from 41.39% to 34.07% for new patients, and from 39.86% to 35.03% for established patients, which represents an increase of 1,148 and 3,199 successful appointments, respectively. A four-week reduction would decrease the missed-appointment rate to 23.98% and 27.45% for new patients and established patients, respectively, or an increase of 2,728 and 8,218 successful appointments.

Type of Patient	Waiting Time Reduction	% No-shows	% Cancellations without Reschedule	% Cancellations with Reschedule	% Missed Appointments	Missed Appointments Reduction
New Patients	Current	14.00%	10.47%	16.92%	41.39%	-
	1 Week	11.23%	9.09%	13.75%	34.07%	1,148
	2 Weeks	9.82%	7.86%	12.43%	30.10%	1,769
	4 Weeks	7.65%	5.94%	10.40%	23.98%	2,728
Established Patients	Current	12.82%	10.71%	16.33%	39.86%	-
	1 Week	11.42%	9.60%	14.02%	35.03%	3,199
	2 Weeks	10.63%	8.73%	12.95%	32.31%	4,997
	4 Weeks	9.22%	7.19%	11.04%	27.45%	8,218

Table 3. Waiting time reduction impact on missed appointments – Scenarios.

Source: prepared by the authors based on hospital data

5. Conclusions & Future Research

This study adds to the literature on appointment waiting times, the analysis of no-shows, and cancellations with and without reschedule separately. Results confirmed the strong impact of long waiting times on patients' appointment-keeping behavior. The logarithmic regression was found as the best-fit function for the correlation between variables for all cases. When analyzing new and established patients separately, we found that the rates of each type of appointment-keeping behavior were similar. However, the correlation analysis showed that new patients tend to miss appointments more often than established patients when the waiting time increases.

The different waiting time reduction scenarios showed the potential for improvement based on missed appointments that could be avoided. We also found that it gets more complicated to reduce missed appointments as the waiting time is reduced. This is due to the patients' appointment distribution. In our case, a large proportion of the appointments were scheduled more than 12 weeks in advance, and missed-appointment rates remain almost constant for long waits. Consequently, a decrease of these patients' waiting times has almost no effect on cancellation and no-show rates.

The methodology applied in this case study can help health care managers to understand initial implications of long waiting times, to make decisions according to reliable data, and to address improvement related to patient satisfaction and hospital performance. Managers could supplement this model with financial data that would allow them to measure the economic impact of the different appointment-keeping behaviors in order to see the benefit of reducing waiting times.

Health care managers could also apply the same methodology to different departments or facilities of the hospital. The most likely outcome is that some areas have longer waiting times than others, and therefore higher rates of cancellations and no-shows. The regression analysis tells hospitals how much they need to reduce waiting times, if they want to reduce the cancellations and no-shows at those specific areas of the hospital with longer waits. A further analysis could evaluate the root-cause of these waits and the necessary measures to reduce the backlog. Managers could use this information to gage how much they need to invest in these measures with how much the profit margin will increase with the reduction of missed appointments.

Finally, future research should also consider that some established patients scheduled appointments a long time in advance due to periodical visits. However, these long waiting times are not due to the hospital's backlog; these long waits are only due to a special treatment or control period. This situation may explain why, in our study, new patients had to wait much less than established patients according to the call-appointment interval used to classify the appointments waiting times. Also, another situation that may

occur is that any patient might schedule an appointment a few days or weeks in advance due to personal reasons, even if there are other available appointments before the scheduled date.

In order to overcome these limitations on waiting time measuring, the first next available appointment (FNA) and the desired date (DD) have been used as two of the waiting time measures that can also predict patient satisfaction (Prentice, Davies & Pizer, 2013). On one hand, the first next available appointment measures the time between the day an appointment is created and the day the first available open appointment slot occurs. On the other hand, the desired date measures the time between when the patient desires the appointment and the first next available appointment from the day the patient wants to be seen. Future researchers could try to find if there is any correlation between these two waiting time measures and the appointment-keeping behavior of the patients, in order to better predict no-shows and cancellations.

References

- American Hospital Association (2015). *Trends in Hospital Financing*. Trendwatch Chartbook 2015: Trends Affecting Hospitals and Health Systems, 2015, 35-42.
<http://www.aha.org/research/reports/tw/chartbook/2015/15chartbook.pdf>. (Accessed: April 2016)
- Bean, A.B., & Talaga, J. (1995). Predicting appointment breaking. *Marketing Health Services*, 15(1), 29.
- Cayirli, T., Yang, K.K., & Quek, S.A. (2012). A Universal Appointment Rule in the Presence of No-Shows and Walk-Ins. *Production and Operations Management*, 21(4), 682-697. <https://doi.org/10.1111/j.1937-5956.2011.01297.x>
- Gallucci, G., Swartz, W., & Hackerman, F. (2005). Impact of the Wait for an Initial Appointment on the Rate of Kept Appointments at a Mental Health Center. *Psychiatric Services*, 56(3), 344-346. <https://doi.org/10.1176/appi.ps.56.3.344>
- Green, L.V. & Savin, S. (2008). Reducing Delays for Medical Appointments: A Queuing Approach. *Operations Research*, 56(6), 1526-1538. <https://doi.org/10.1287/opre.1080.0575>
- Green, L.V. & Yankovic, N. (2011). Identifying good nursing levels: a queuing approach. *Operations Research*, 59(4), 942-955. <https://doi.org/10.1287/opre.1110.0943>
- Green, L.V. (2010). Queuing theory and modelling. In Yih, Y. (Ed.), *Handbook of healthcare delivery systems* (1-16). Florida: CRC Press.

- Guzek, L.M., Gentry, S.D., & Golomb, M.R. (2015). The Estimated Cost of “No-Shows” in an Academic Pediatric Neurology Clinic. *Pediatric Neurology*, 52(2), 198-201.
<https://doi.org/10.1016/j.pediatrneurol.2014.10.020>
- Healthcare Information and Management Systems Society (2013). *Healthcare Provider Innovation Survey*. <http://s3.amazonaws.com/rdcms-himss/files/production/public/innovation-survey-full-results.pdf> (Accessed: April 2016)
- Jatulis, D.E., Bundek, N.I., & Legorreta, A.P. (1997). Identifying predictors of satisfaction with access to medical care and quality of care. *American Journal of Medical Quality*, 12(1), 11-17.
<https://doi.org/10.1177/0885713X9701200103>
- Kumar, C., Norris, J.B., Chand, S., Moskowitz, H., Shade, S.A., & Willis, D.R. (2014). An empirical investigation into factors affecting patient cancellations and no-shows at outpatient clinics. *Decision Support Systems*, 57, 428-443. <https://doi.org/10.1016/j.dss.2012.10.048>
- Liu, N. (2016). Optimal Choice for Appointment Scheduling Window under Patient No-Show Behavior. *Production and Operations Management*, 25(1), 128-142. <https://doi.org/10.1111/poms.12401>
- Macharia, W.M., Leon, G., Rowe, B.H., Stephenson, B.J., & Haynes, R.B. (1992). An overview of interventions to improve compliance with appointment keeping for medical services. *JAMA*, 267(13), 1813-1817. <https://doi.org/10.1001/jama.1992.03480130129038>
- Mardiah, F.P., & Basri, M.H. (2013). The Analysis of Appointment System to Reduce Outpatient Waiting Time at Indonesia’s Public Hospital. *Human Resource Management Research*, 3(1), 27-33.
- Merritt Hawkins (2014). Survey of Physician Appointment Wait Times and Medicaid and Medicare Acceptance Rates.
<http://www.merrithawkins.com/uploadedFiles/MerrittHawkings/Surveys/mha2014waitsurvPDF.pdf>. (Accessed: April 2016)
- Murray, M.M., & Tantau, C. (2000). Same-day appointments: exploding the access paradigm. *Family practice management*, 7(8), 45-45.
- Pesata, V., Pallija, G., & Webb, A.A. (1999). A descriptive study of missed appointments: families’ perceptions of barriers to care. *Journal of Pediatric Health Care*, 13(4), 178-182. [https://doi.org/10.1016/S0891-5245\(99\)90037-8](https://doi.org/10.1016/S0891-5245(99)90037-8)

Prentice, J.C., Davies, M.L., & Pizer, S.D. (2013). Which outpatient wait-time measures are related to patient satisfaction? *American Journal of Medical Quality*, 29(3), 227-235.

<https://doi.org/10.1177/1062860613494750>

Weingarten, N., Meyer, D.L., & Schneid, J.A. (1997). Failed appointments in residency practices: who misses them and what providers are most affected? *The Journal of the American Board of Family Practice*, 10(6), 407-411.

Wilson-Witherspoon, P., Moore, C.G., & Probst, J.C. (2001). Time and money: effects of no-shows at a family practice residency clinic. *Family Medicine*, 33(7), 522-527.

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