

Pyelonephritis Treatment: An analysis of outcomes between teaching & non-teaching hospitals

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I. Introduction

Pyelonephritis is a serious kidney infection that occurs when a urinary tract infection spreads from the bladder to the kidneys. If left untreated, pyelonephritis can cause life threatening complications, including blood septicemia as a result of the bacteria traveling through the bloodstream and permanent kidney scarring leading to chronic kidney disease, high blood pressure or kidney failure. While it can usually be treated outpatient with antibiotics, inpatient treatment is sometimes necessary in severe cases. Pyelonephritis can be cured with proper treatment; however, research has found that pyelonephritis has a mortality rate of up to 10 – 20% (Belyayeva, 2021).

Out of the approximate 250,000 acute cases of pyelonephritis each year, an estimated 100,000 cases result in hospitalization (Ramakrishnan, 2005). Studying factors related to optimal treatment of acute cases is necessary to determine best courses of treatment and thus to reduce disease burden; teaching or non-teaching status of the treating hospital is of particular interest. Existing literature suggests that as teaching hospitals provide higher quality care (Ayanian, 2002), they may be protective in terms of mortality (Burke, 2017) and also may exhibit patterns of shorter hospital stays, (Rebekah, 2021) which are critical factors of concern in the treatment of acute pyelonephritis. This study seeks to determine the impact of receiving treatment for pyelonephritis at a teaching hospital on length of stay and on mortality. Consistent with the literature, we hypothesize that receiving treatment at a teaching hospital is associated with shorter length of stay and lower mortality.

II. Materials and Methods

This study examines the impact of teaching hospital status on two outcomes: odds of death and length of stay, categorized by greater than or, less than or equal to, seven days. The study population is restricted to those who received treatment for pyelonephritis. Missing data were appropriately managed ($n = 1$), and the total sample size included for analysis was 6,117 participants. The sample is drawn from the National Inpatient Sample (NIS). NIS is part of a family of databases for the Healthcare Cost and Utilization project—the largest collection of longitudinal hospital care data in the United States. Data in the NIS database are sampled from state inpatient databases that includes all inpatient data contributed to the Healthcare Cost and Utilization project.

To investigate our research question, we used propensity score methodology, specifically propensity score matching. A propensity score is the probability of receiving treatment at a teaching hospital as a function of measured baseline factors. The purpose of the propensity score matching method is to match patients who received treatment for pyelonephritis at a teaching hospital to those who received treatment at a non-teaching hospital with respect to propensity score and covariates. This addresses any lack of balance between baseline factors among those in the exposure group and those in the control group.

The propensity score matching method is a two-step method. In the first step, a propensity score is calculated for each observation using logistic regression models. The treatment (i.e., being treated at a teaching hospital) is regressed on baseline factors. The baseline factors to be included were determined through a theoretical and statistical evaluation of confounding, which included a thorough literature review. If the published literature revealed probable confounding of a given covariate, it was included in the regression model. Age was recategorized from a continuous to a

categorical variable based on the distribution of observations across treatment groups and outcomes.

Once covariates were chosen, two prediction models were developed to calculate propensity scores. The first model is a no interaction model, whereby covariates were included without interaction terms. The second model included all possible two way interaction terms. Because the model converged upon initial fitting, backwards selection and a significance level requirement were not needed.

Once the models were created to calculate propensity scores, the Greedy 5 to 1 matching method was used in order to achieve covariate balance between the treatment and control groups. This algorithm matches those who did not receive treatment at a teaching hospital to those who did receive at a teaching hospital in a sequential fashion based on propensity score. With greedy matching, a subject who received treatment at the teaching hospital is first selected at random. Then, the patient who did receive treatment at a non-teaching hospital whose propensity score is closest to the randomly selected patient who received treatment at the teaching hospital (up to 5 digits) is chosen for matching to this treated subject. The process is repeated with five digits down to one digit until all patients from teaching hospitals who can be matched have been matched to the closest-matching patient. Any unmatched observations are discarded from the dataset.

After matching is complete, balance of covariates across treatment groups were measured through calculating standardized differences based on the step 1 model with and without interaction terms. The model that had the smallest standard differences is selected to create the outcome models for both death and length of stay. These methods were conducted via SAS using a significance level of 0.05.

There are a few major assumptions in our methods. Most importantly, in order to use the propensity score methodology, there must be overlap in subject profiles between the treatment and control groups. This approach does not require the assumption that baseline factors are similarly distributed across treatment groups in the original cohort, as the use of the propensity score methodology accounts for this lack of balance.

III. Results

Within the original cohort, 6,117 observations were analyzed. The original sample was 80.19% female and 19.81% male, and 51.51% of the patients were white. The mean age of the cohort was 47.08 and the median age was 47 years. When age was converted to a categorical variable, 42.90% of the original cohort was under the age of 40.

When the original cohort was stratified by teaching hospital status, 57.46% of patients treated at non-teaching hospitals were white, compared with 43.71% of patients at teaching hospitals. Within non-teaching hospitals, 80.75% of patients were female compared to 79.45% within teaching hospitals. When examining age, 40.09% of observations were under the age of 40 at non-teaching hospitals, while that number increased to 46.58% at teaching hospitals. Similarly, 27.29% of patients were 70 or older at non-teaching hospitals, compared to 19.53% at teaching hospitals. Interestingly, 75.99% of non-teaching hospitals were located in an urban area, compared to 97.51% of teaching hospitals.

Table 1: Baseline factors in the original cohort by exposure category

	Teaching status of hospital				Chi-Squared p-value
	0		1		
	N	%	N	%	
Age Group					<0.0001
<40	1391	40.09	1233	46.58	
40-50	331	9.54	291	10.99	
50-60	389	11.21	337	12.73	
60-70	412	11.87	269	10.16	
70+	947	27.29	517	19.53	
Year of Treatment					0.3081
2007	678	19.54	472	17.83	
2008	677	19.51	496	18.74	
2009	703	20.26	551	20.82	
2010	656	18.9	539	20.36	
2011	756	21.79	589	22.25	
Race					<0.0001
White	1994	57.46	1157	43.71	
Black	295	8.5	411	15.53	
Hispanic	489	14.09	506	19.12	
Other	188	5.42	175	6.61	
Unknown	504	14.52	398	15.04	
Insurance					<0.0001
Medicare	1291	37.2	762	28.79	
Medicaid	734	21.15	716	27.05	
Private Insurance	1029	29.65	778	29.39	
Other	416	11.99	391	14.77	
Sex					0.2060
Male	668	19.25	544	20.55	
Female	2802	80.75	2103	79.45	
Hospital Location					<0.0001
Rural	833	24.01	66	2.49	
Urban	2637	75.99	2581	97.51	
Hospital Region					<0.0001
Northeast	361	10.4	580	21.91	
Midwest	658	18.96	572	21.61	
South	1519	43.78	962	36.34	
West	932	26.86	533	20.14	

In examining the matched cohort, 45.62% of patients in both teaching hospitals and non-teaching hospitals were less than 40 years old, while approximately 22% of patients in both hospital types were age 70 or above. Additionally, approximately 52% of patients in both hospital types were white and approximately 81% of patients receiving treatment at each hospital type were female. This balance of baseline covariates across treatment and non-treatment groups indicates that the propensity score matching method was properly executed.

Table 2: Baseline factors in the matched cohort by exposure category

	Teaching status of hospital				Chi-Squared p-value
	0		1		
	N	%	N	%	
Age Group					0.9898
<40	937	45.62	937	45.62	
40-50	209	10.18	199	9.69	
50-60	241	11.73	244	11.88	
60-70	220	10.71	222	10.81	
70+	447	21.76	452	22.01	
Year of Treatment					0.9580
2007	393	19.13	389	18.94	
2008	359	17.48	377	18.35	
2009	425	20.69	424	20.64	
2010	408	19.86	408	19.86	
2011	469	22.83	456	22.2	
Race					0.9522
White	1070	52.09	1064	51.8	
Black	212	10.32	220	10.71	
Hispanic	357	17.38	350	17.04	
Other	112	5.45	105	5.11	
Unknown	303	14.75	315	15.34	
Insurance					0.9771
Medicare	638	31.06	629	30.62	
Medicaid	501	24.39	498	24.25	
Private Insurance	654	31.84	667	32.47	
Other	261	12.71	260	12.66	
Sex					0.8110
Male	391	19.04	385	18.74	
Female	1663	80.96	1669	81.26	
Hospital Location					0.7195
Rural	62	3.02	66	3.21	
Urban	1992	96.98	1988	96.79	
Hospital Region					0.9088
Northeast	306	14.9	318	15.48	
Midwest	407	19.81	416	20.25	
South	860	41.87	841	40.94	
West	481	23.42	479	23.32	

Based on a crude logistic model, those treated at a teaching hospital had, on average, 1.004 (95% CI: 0.823, 1.223) times the odds of death as those treated at a non-teaching hospital. When adjusting for age group, year of treatment, race, insurance status, sex, hospital location, and hospital region, those who were treated at a teaching hospital had 1.319 (95% CI: 1.052, 1.653) times the odds of death, on average, compared to those who were treated at a non-teaching hospital.

Finally, using the step one propensity score model with any two-way interaction term and the propensity score matching method, those who were treated at a teaching hospital had, on average, 1.147 (95% CI: 0.894, 1.471) times the odds of death compared to those treated at non-teaching hospitals.

Furthermore, those treated at a teaching hospital had, on average, 1.206 (95% CI: 1.050, 1.385) times the odds of a length of stay longer than 7 days, compared to those treated at a non-teaching hospital. When adjusting for age group, year of treatment, race, insurance status, sex, hospital location, and hospital region, those who were treated at a teaching hospital had 1.219 (95% CI: 1.041, 1.426) times the odds of a length of stay longer than 7 days, on average, compared to those treated at a non-teaching hospital. Finally, using the step one propensity score model with any two-way interaction term and the propensity score matching method, those who were treated at a teaching hospital had, on average, 1.008 (95% CI: 0.849, 1.197) times the odds of a length of stay longer than 7 days compared to those treated at non-teaching hospitals.

Table 3: Crude, Adjusted, and PS-Matched Odds Ratios for both outcomes

Outcome	Crude Model [OR (95% CI)]	Multivariable Model [OR (95% CI)]	PS Match Model [OR (95% CI)]
Death	1.004 (0.823, 1.223)	1.319 (1.052, 1.653)	1.147 (0.894, 1.471)
Length of Stay (> 7 days)	1.206 (1.050, 1.385)	1.219 (1.041, 1.426)	1.008 (0.849, 1.197)

IV. Discussion

This study was based on more than 6,000 patients who received inpatient treatment for pyelonephritis and compared the outcomes of those who received the treatment at a teaching hospital to those who did not receive treatment at a teaching hospital. Contrary to the hypothesis, the results indicate that there is no association between the exposure—a hospital’s teaching status—and the outcomes, mortality and length of stay. This means that the odds of having a length of

stay longer than seven days and the odds of mortality between patients at teaching hospitals was not statistically different from those of patients at non-teaching hospitals, on average, based on these data.

Our hypothesis was formed through literature review that indicated teaching hospital status was associated with lower mortality rates for common conditions compared with non-teaching hospitals (Ayanian, 2002). Additionally, research prior to analysis showed that pyelonephritis tended to resolve within a median of 3 days if proper antibiotic treatment was administered in a timely fashion (Chan, 2021). Thus, we hypothesized that given teaching hospitals tend to have higher quality of care, the length of stay would thus be likely shorter. Between lack of statistical significance in our results and literature review post-analysis, we found that there may be an even more influential factor that affects the length of stay and mortality for pyelonephritis patients than access to timely antibiotic treatment. A significant factor for longer hospital stays for those diagnosed with pyelonephritis was from complications of the infection itself. Those diagnosed with complicated pyelonephritis had significantly longer hospital stays compared to those who had uncomplicated pyelonephritis. Moreover, those with complicated disease tended to be much older than those with uncomplicated disease; a previous study calculated a mean difference in age of 17 years (Agara, 2017). In other words, length of hospital stay and age, one of the covariates in our propensity score model, are associated with severity of pyelonephritis. The potential impact of not accounting for disease severity on our results could have affected the generalizability. Additionally, the inability to adjust for unmeasured confounding is one of the major disadvantages of using propensity score methods. Propensity score methodology can only deal with measured covariates, but does not balance groups on unmeasured covariates. Thus, any unmeasured covariates that could be a significant confounder could greatly impact the generalizability and

validity of our results. In summary, our major limitations include the potential for unmeasured confounding and the lack of distinction in the data between complicated and uncomplicated pyelonephritis. Future research should account for the severity of disease by indicating presence or absence of complications.

REFERENCES

- (1) Belyayeva M, Jeong JM. Acute Pyelonephritis. [Updated 2021 Jul 10]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2022 Jan-. Available from: <https://www.ncbi.nlm.nih.gov/books/NBK519537/>
- (2) Ayanian, J. Z., & Weissman, J. S. (2002). Teaching hospitals and quality of care: a review of the literature. *The Milbank quarterly*, 80(3), 569–v. <https://doi.org/10.1111/1468-0009.00023>. Retrieved from <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2690120/#:~:text=In%20summary%2C%20the%20largest%20and,care%20than%20do%20nonteaching%20hospitals>.
- (3) Jia H, Li L, Li W, Hou T, Ma H, Yang Y, Wu A, Liu Y, Wen J, Yang H, Luo X, Xing Y, Zhang W, Wu Y, Ding L, Liu W, Lin L, Li Y, Chen M. Impact of Healthcare-Associated Infections on Length of Stay: A Study in 68 Hospitals in China. *Biomed Res Int*. 2019 Apr 18;2019:2590563. doi: 10.1155/2019/2590563. PMID: 31119159; PMCID: PMC6500696.
- (4) Freeman WJ (AHRQ), Weiss AJ (IBM Watson Health), Heslin KC (AHRQ). Overview of U.S. Hospital Stays in 2016: Variation by Geographic Region. HCUP Statistical Brief #246. December 2018. Agency for Healthcare Research and Quality, Rockville, MD. www.hcup-us.ahrq.gov/reports/statbriefs/sb246-Geographic-Variation-Hospital-Stays.pdf
- (5) Ramakrishnan K, Scheid DC. Diagnosis and management of acute pyelonephritis in adults. *Am Fam Physician*. 2005 Mar 1;71(5):933-42. Erratum in: *Am Fam Physician*. 2005 Dec 1;72(11):2182. PMID: 15768623.
- (6) Burke LG, Frakt AB, Khullar D, Orav EJ, Jha AK. Association Between Teaching Status and Mortality in US Hospitals. *JAMA*. 2017;317(20):2105–2113. doi:10.1001/jama.2017.5702
- (7) Rebekah J. Walker, Ankur Segon, Jennifer Good, Sneha Nagavally, Navdeep Gupta, Doug Levine, Joan Neuner & Leonard E. Egede (2021) Differences in length of stay by teaching team status in an academic medical center in the Midwestern United States, *Hospital Practice*, 49:2, 119-126, DOI: [10.1080/21548331.2021.1882238](https://doi.org/10.1080/21548331.2021.1882238)
- (8) Hadley J, Yabroff KR, Barrett MJ, Penson DF, Saigal CS, Potosky AL. Comparative effectiveness of prostate cancer treatments: evaluating statistical adjustments for confounding in observational data. *J Natl Cancer Inst*. 2010 Dec 1;102(23):1780-93. doi: 10.1093/jnci/djq393. Epub 2010 Oct 13. PMID: 20944078; PMCID: PMC2994860.
- (9) Stukel TA, Fisher ES, Wennberg DE, Alter DA, Gottlieb DJ, Vermeulen MJ. Analysis of observational studies in the presence of treatment selection bias: effects of invasive cardiac management on AMI survival using propensity score and instrumental variable methods. *JAMA*. 2007 Jan 17;297(3):278-85. doi: 10.1001/jama.297.3.278. PMID: 17227979; PMCID: PMC2170524.
- (10) Austin P. C. (2011). An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate behavioral research*, 46(3), 399–424. <https://doi.org/10.1080/00273171.2011.568786>
- (11) Burke, L. G., Frakt, A. B., Khullar, D., Orav, E. J., & Jha, A. K. (2017). Association between teaching status and mortality in US hospitals. *Jama*, 317(20), 2105-2113.

- (12) Chan, H. T. C., Leung, L. Y., Law, A. K. K., Cheng, C. H., & Graham, C. A. (2021). Predictive factors for prolonged hospitalisation in acute pyelonephritis patients admitted to the emergency medicine ward. *Hong Kong Journal of Emergency Medicine*, 10249079211000976.
- (13) Agara, L., & JL, B. A. (2017). Acute complicated and uncomplicated pyelonephritis in the emergency department: process-of-care indicators and outcomes. *Emergencias: revista de la Sociedad Espanola de Medicina de Emergencias*, 29(1), 27-32.