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Identifying the Factors Associated With Inpatient Admissions for Non-COVID-19 Illnesses:

Application of Regression Analysis and NFL Theorem

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ABSTRACT

Declining inpatient admissions have serious consequences on hospital financial stability as well as the health of patients. Thus, identifying factors associated with inpatient admissions is crucial to properly manage healthcare services. The major objective of this research is to demonstrate a systematic methodology using regression analysis and no free lunch (NFL) theorem to identify the most significant factors associated with non-COVID-19 ADMs and to identify which of them have deviated from an ideal state of service. This research uses Pennsylvania U.S. hospital data from 2003 to 2018 and identified that bed setup, staffed and supported, average length of stay, occupancy rate, readmission index, and outpatients are significantly associated with ADMs. Further, readmissions and outpatient admissions are found with an unusual association compared to an ideal condition. This paper discusses the steps that U.S. healthcare systems have already implemented and presents improvement recommendations.

KEYWORDS

Average Length of Stay, Beds Setup Staffed Supported, Inpatient Admissions, No Free Lunch Theorem, Non-COVID-19 Illnesses, Occupancy Rate, Outpatient Admissions, Readmission Index, Regression Analysis

INTRODUCTION

The fact that there was an obvious decline in hospital inpatient admissions in the recent past and that America had fewer physician visits than most of its peer industrial countries is no longer a secret (Tikkanen, 2017). For instance, between 2005 and 2014 the rate of inpatient stays per 100,000 population significantly decreased across all age groups across America (McDermott et al., 2017). Another study reported that rural hospitals experienced an average change in inpatient average daily census of -13% between 2011 and 2017(Malone et al., 2021). According to more recent Epic Health Research Network's data, hospital admissions remained below expected levels in 2021(Gallagher et al., 2021). Gallagher et al. (2021) further mention that, over the first quarter of 2021, hospital admission rates were 89.4% of what would have been expected in the absence of the pandemic. The authors clearly mention that even if patients with a COVID-19 diagnosis are removed, all other admissions

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are 80.7% of expected levels based. After analyzing Epic Health Research Network's admissions data by age, Heist et al. (2021) reported that non-COVID-19 admissions for patients aged 65 and older were just in the range of 53.4-63.0% of predicted levels in April 2020, compared to 68.6-75.1% of predicted levels for younger patients. Their broader study involving data from 47 states showed that hospitals in the Northeast had experienced the steepest decline in non-COVID-19 admissions early in the pandemic, although non-COVID-19 admissions remained at a higher level than other regions in the fall of 2020. The trend is likely to continue, according to an article on a Moody's investors service data analysis (Kelly, 2022). The author states that Tenet, which has been building its outpatient business through its United Surgical Partners unit, reported a 9% rise in outpatient visits during the fourth quarter 2021, even if total admissions declined 4% from the year before. HCA Healthcare saw patient volumes increase in most categories during the period, except for inpatient services (Kelly, 2022).

According to Heist et al. (2021), decline in inpatient admissions could create serious negative consequences on patients' health, as well as on hospitals' financial stability. As per Tikkanen (2017), even though Americans use some expensive technologies such as Magnetic resonance imaging outperforms its peers in terms of preventive measures, the U.S. still have the lowest life expectancy, highest suicide rate, highest chronic disease burden, and highest obesity rate among industrialized countries. Tikkanen (2017) specifically mentioned that this can be because Americans have had fewer physician visits than their peers in most industrialized countries. The resulting falling levels of non-COVID-19 admissions suggest that people may be delaying care in ways that could be harmful to their long-term health, and the impact of that forgone care should be an important subject of future analysis (Heist et al., 2021). Besides, older patients who were at a higher risk of serious illness or death due to COVID-19 were more reluctant than younger patients to enter a hospital, if not necessary (Heist et al., 2021). A recent study presents similar findings speculates that the declines in medical admissions may have been due in part to a fear of contracting COVID-19 by both physicians and patients, greater use of telemedicine, and possibly lower transmission rates of non-COVID-19 diseases following stay-at-home orders (Dartmouth Giesel School of Medicine, 2020).

As already mentioned, another crucial impact of overall ADMS decline is on the continuity of healthcare provider services. Probing more on the financial instability, in a recent study, Gallagher et al. (2021) found that the median hospitals had enough cash on hand to pay their operating expenses for 53 days in 2018, but the 25th percentile hospitals only had enough cash on hand for eight days. According to Kelly (2022), the latest data from the Bureau of Labor Statistics show that the home health services sector added 20,000 positions in February 2020 alone, while, overall, healthcare employment was down of 2% as compared to two years before. The authors further state that smaller hospitals, public hospitals, and rural hospitals may therefore be at risk of closing or merging, if they do not have the financial resources to make up for declines in revenue caused by the declines in admissions. For instance, recently, Tyler Memorial Hospital in Pennsylvania has announced it will end acute inpatient care and surgical and emergency department services (Ellison et al., 2021). Hospital closures have become a national concern since, out of 2,000 rural U.S. hospitals, 150 have closed since 2005, and more than 300 are at risk. Such hospital closures generate severe negative health and economic repercussions due to the loss of local acute care services (Tachibana, 2022). It ends up leading to increased travel time to distant alternative facilities (Capps et al., 2010), unemployment for healthcare workers (Holmes et al., 2006), discourage other financial investments in rural communities, worsen general poverty conditions, and thus stagnate the local economies (Probst et al., 1999). As Tachibana (2022) stated, when a rural hospital closes, it can disrupt both the health care and the economy of a community, as the health care sector can supply as much as 10% of the jobs in a rural area. According to Chatterjee et al. (2022), the extent to which recent hospital closures may impact local economies and the extent to which adverse economic trends may presage closures is not well understood. According to the authors, although some prior studies on rural hospital closures through 1999 showed short-term and area-level declines in per capita income and increases in unemployment, some local reports from such communities suggest that existing economic decline and joblessness were important factors that drove hospitals closures in the first place. Therefore, Chatterjee et al. (2022) suggested that rural hospital closures may be a symptom of economic decline, as well as a potential driver.

It is very clear that identifying factors associated with inpatient admissions are important for managing the healthcare services efficiently. Prior research delved into inpatient admissions due to different diseases (Berry et al., 2018; Green et al., 2002; Green et al., 2016; Kaye et al., 2015). Yet, little research is available on general inpatient admissions due to non-COVID-19 illnesses. Therefore, the objective of this research was to demonstrate a systematic methodology using regression analysis to identify the most significant factors associated with non-COVID-19 inpatient admissions, as well as to identify which of them have considerably deviated from an ideal service state. To achieve this objective, the authors used random effects (RE) regression, pooled ordinary least squares (POLS) regression, and fixed effects (FE) regression models on Pennsylvania, USA, hospital data during the period 2003-2018 to ensure non-COVID-19 illnesses. After comprehensive statistical analysis and the use of no free lunch (NFL) theorem, the authors identified factors associated with inpatient admissions that appeared significant across all the regression models used. Then, the authors compared the significant regression effects these regression models generated with the preferred healthcare service performance levels of an imaginary ideal state of healthcare performance. Accordingly, the authors made the recommendations pertaining to the scope of the research.

LITERATURE REVIEW

The authors conducted an extensive literature search to generate the specific theoretical framework of this research using the main variables associated with non-COVID-19 inpatient admissions. Some of the key variables included in the study are consistent with existing literature in the healthcare, and operations management areas are (Deily et al., 2000; Kim, 2010; Mullner et al., 1986; Pai et al., 2019):

- **Beds Set Up and Staffed**: A better indicator of hospital capacity compared with licensed beds.
- **Average Length of Stay:** An important indicator of hospital performance often used in the assessment of quality of care, costs, and efficiency.
- **Occupancy Rate:** A measure of hospital utilization.
- **Casemix Index:** Used to capture the complexity of operation of a hospital.
- **Structure:** Hospitals categorized as either for-profit and not-for-profit.
- **Teaching Status:** As teaching hospitals are generally resource-intensive and may incur higher operating expenses because they are affiliated with medical schools, located in urban areas, treat the most complex patients' cases and the urban underserved population, train physicians and other health professionals, and advance research (Shahian et al., 2012).
- **Location (Rural or Urban):** The empirical evidence shows impacts hospital performance (Younis, 2003; McKay et al., 2008).

To account for the effect of quality of care on hospital admissions, the authors considered three indicators: Readmission index, mortality index, and full-time equivalent registered nurses per bed. The first two indicators measure outcome quality by taking a weighted average of risk-adjusted readmissions rate and risk-adjusted mortality rate, respectively, for 11 common medical procedures and treatments identified by ICD-9-CM (i.e., International Classification of Diseases, Ninth Revision, Clinical Modification) codes for hospitals in Pennsylvania. The authors used the following procedures and treatments: Abnormal heartbeat, chest pain, chronic obstructive pulmonary disease, congestive heart failure, diabetes, gallbladder removal, heart attack, hypotension, kidney failure, pneumonia, and stroke. They computed the weighted outcome quality index as follows (Pai et al., 2019):

$$Mortality\,Index_{ht} = \frac{\sum c_{pht} RAM_{pht}}{C_{ht}} \;\; \forall h \tag{1}$$

$$Readmission\,Index_{ht} = \frac{\sum c_{pht} RAR_{pht}}{C_{ht}} \;\; \forall h \tag{2}$$

RAM_{pht} captures the risk-adjusted mortality rate from the p^{th} procedure for the h^{th} hospital in year t. Similarly, RAR_{pht} captures the risk-adjusted readmission rate from the p^{th} procedure for the h^{th} hospital in year t. c_{pht} captures number of cases in p^{th} procedure for the h^{th} hospital in year t. C_{ht} captures the total number of cases across all the 11 procedures.

The landmark report of the Institute of Medicine's Committee on the Adequacy of Nurse Staffing in Hospitals and Nursing Homes noted: "Nursing is a critical factor in determining the quality of care in hospitals and the nature of patient outcomes" (Davis et al., 1996, p.92). A growing body of evidence demonstrates that higher registered nurse staffing was associated with reduced adverse events, improved patient safety, shorter lengths of stay, reduced costs, and decreased risk of hospital-related death (Everhart et al., 2013; Kane et al., 2007; Stone et al., 2007). Therefore, registered nurse per bed was included as the third indicator of quality of care.

In this study, the authors controlled for payer mix, which in this work is the percentage of net patient revenue coming from Medicare and Medicaid. It is important because Medicare and Medicaid typically pay hospitals less than what it costs them to treat. The authors also controlled for percentage of bad debt and charity care, as both are known to inflate hospital operating expenses and to be highly correlated with not-for-profit status (Ding, 2014). In the Pennsylvania Health Care Cost Containment Council's (2022) data set, both bad debt and charity care were combined; hence, bad debt and charity care were treated as a single variable. Also, there is an increasing trend of outpatient admissions, which include emergency room (ER)visits. According to Schuur and Venkatesh (2012), there is an increasing use of ER for inpatient admissions, and this impacts quality of care, care coordination, and payments. Therefore, the authors included the variable outpatients in their model. In addition, they included three socioeconomic and demographic variables which provide information about the county in which the hospital is located: Percentage of residents who are age 65 or older, population per square mile, and per capita income. Besides, they included the variables operating margins, which is a popular metric for determining hospital profitability, and Herfindahl-Hirschman index, which is a commonly accepted measure of market concentration. Table 1 presents the operational definitions and a summary of the key descriptive statistics of the variables the authors used in their research.

Table 1. Operational definitions of the variables used (Note: All measures for one year)

Variable	Operational Definition	Mean	SD
Inpatient Admissions, ADMS	Patients admitted to the hospital to stay overnight, whether briefly or for an extended time (does not include patients with observatory status). Include both direct admissions and the admissions through the emergency department.	6,371	5,860
Beds Setup, Staffed, and Supported, BEDSSS	The number of beds available for use by patients at the end of the cost reporting period. A bed means an adult bed, pediatric bed, birthing room, or newborn bed maintained in a patient care area for lodging patients in acute, long term, or domiciliary areas of the hospital.	209.49	198.99

Table 1 continued on next page

Table 1 continued

Variable	Operational Definition	Mean	SD
Average Length of Stay (Days), AVGLOS	Average number of days patients spent in the hospital for all inpatients discharged over a given period.	4.69	0.95
Occupancy Rate, ORATE	The rate of how many hospital beds is used at any given period. To calculate, Inpatient Days of Care is divided by the Bed Days Available and is multiplied by 100, where Bed Days Available is the maximum number of inpatient days of care.	58.27	16.80
Casemix Index, CASEMIX	The average amount of resources consumed per Medicare inpatient case at a hospital. Hospitals that tend to treat more resource-intensive (i.e., severe) cases will have a higher calculated CMI.	1.40	0.28
Structure (For-profit = 1), STRUCDUM	Whether a hospital is categorized as either for-profit or not-for-profit	0.85	0.36
Teaching Status (Yes = 1), TEACHDUM	Whether a hospital is a teaching or a nonteaching hospital	0.20	0.40
Location (Urban = 1), LOCDUM	Whether a hospital is located in an urban or a rural area	0.58	0.49
Readmission Index, REINDEX	The weighted average of risk-adjusted readmission rate	11.06	9.11
Mortality Index, MORINDEX	Weighted average of risk-adjusted mortality rate	1.85	1.73
Registered Nurses per Bed, RNSPBED	The number of full-time equivalent registered nurses per occupied bed. A registered nurse is a nurse graduated from a nursing program and met the requirements outlined by a country, state, province, or similar government-authorized licensing body to obtain a nursing license	1.62	0.56
Medicaid % of NPR, MCNPR	The percentage of net patient revenue coming from Medicare payments	9.85	8.02
Medicare % of NPR, MANPR	The percentage of net patient revenue coming from Medicaid payments	42.65	9.21
Bad Debt and Charity Care, BDCC	The percentage of bad debt and charity expenses during the given period	2.64	1.40
Outpatients, OUTPAT	Number of patients who doesn’t require hospitalization including emergency care when you leave on the same day you arrive, and instances where doctors assign patients under an observatory status not exceeding 24 hours	85,605	70,671
% Population over 65 years, POPO65	Average percentage of population who are above 65 years	16.42	2.31
Population per Square Mile, POPPSM	Average number of people who reside in a square mile of the during a year	1,674	3,302
Per Capita Income, PCINC	Average income earned per person in a given county in a specific year	37,085	11,510
Operating Margins, OPMAR	This profitability indicator to measures the extent to which the organization is using its financial and physical assets to generate a profit	1.47	9.50
Herfindahl Index, HHI	Herfindahl–Hirschman Index/HHI-score, is a measure of the size of firms in relation to the industry they are in and an indicator of the amount of competition among them	0.10	0.04

Below is the authors' main theoretical model specification:

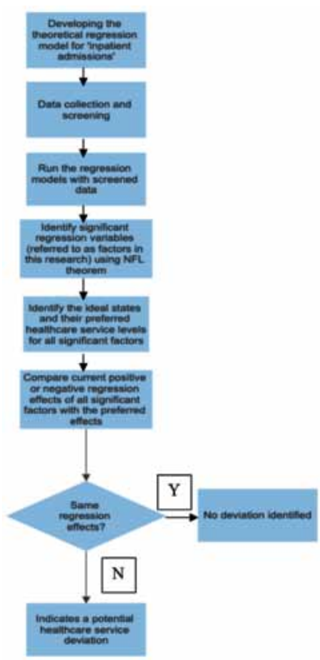
$$Inpatient\,Admissions_{it} = \varkappa_{it}\beta_{x} + \alpha_{i} + \delta_{t} + \varepsilon_{it} \quad (3)$$

In this model, x_{it} was a *k * 1* vector of time-variant variables, β_x was the regression coefficient of x_{it}, α_i represented product-specific and time-invariant characteristics, δ_t represented the year FE, and ε_{it} was the random disturbance term. ε_{it} with strict exogeneity ($E\left(\varepsilon|x\right) = 0$), exhibit $\varepsilon_{it} \sim i.i.d\left(0,\sigma_{\varepsilon}^{2}\right)$, $var\left(\boldsymbol{x}_{it}^{'}\right) = \sigma_{x}^{2}$, $cov\left(\varepsilon_{it}, x_{it}\right) = 0$, $cov\left(\alpha_{it}, x_{it}\right) \neq 0$, $cov\left(\delta_{t}, x_{it}\right) \neq 0$, $cov\left(\varepsilon_{it}, \alpha_{i},\right) = 0$, $cov\left(\varepsilon_{it}, \delta_{t},\right) = 0$.

METHODOLOGY

Figure 1 presents an overview of the methodology the authors adopted in this research and it is followed by detailed subsections.

Figure 1. Systematic research methodology



Theoretical Model

Usually, the distribution of data, relative skewness, and the presence of extreme values all warrant thorough investigation of the data, and it is strongly recommended in literature to pick multiple models which best address each situation (Bhattarai & OptumHealth, 2013). Thus, the authors used several regression analysis models, namely: RE regression, POLS regression, and FE regression, and serial association corrected regression models. ADMS was the dependent variable, and several variables were explanatory independent variables. ADMS is defined as the number of patients admitted to the hospital to stay overnight, whether briefly or for an extended time (it does not include patients with observatory status). This includes both direct admissions and the admissions through the emergency department. Below is the complete theoretical regression model specification with the variables selected for the study. Table 1 provides definitions of all the variables the authors used in the regression models. REGION stands for the hospital region at which the data are originated (Figure 2).

$$\text{ADMS} = \text{BEDSSS} + \text{AVGLOS} + \text{ORATE} + \text{CASEMIX} + \text{STRUCDUM} + \text{LOCATDUM} + \text{TEACHDUM} + \text{REINDEX} + \text{MORINDEX} + \text{RNSPBED} + \text{MCNPR} + \text{MANPR} + \text{POPPSM} + \text{PCPINC} + \text{PCTO65} + \text{OPMAR} + \text{HHI} + \text{OUTPAT} + \text{REGION} \tag{4}$$

Data Collection and Screening

The authors collected data for this research for the years 2003-2018 from several different sources: 1) Pennsylvania Healthcare Cost Containment Council Hospital Performance Reports and Pennsylvania Department of Health, which provide data pertaining to financial analysis, health performance, and hospital utilization; 2) Centers for Medicare and Medicaid Services (CMS) cost reports, which provide data pertaining to case mix index; 3) County Health Profiles, which provide socioeconomic and demographic data. The authors excluded from their analysis hospitals that got closed during the study period. The Pennsylvania data are a good representative for this study for several reasons: Pennsylvania is the home to the nation's third-largest rural population, and it has the third-largest population of elderly in the USA. According to the most recent American Community Survey, the racial composition of Pennsylvania is roughly like that of the U.S. The level of uninsured nonelderly as well as the distribution of population by federal poverty level of Pennsylvanians as of 2018 was roughly the same as that of the national average. Also, Pennsylvania hospitals are spread over nine hospital regions consisting of counties (Figure 2). Thus, the dataset the researchers obtained was rich and representative of a diverse population with several different hospital structures. Although their dataset was from 2003 to 2020, they purposefully limited the data sample to up to 2018 to avoid any COVID-19 inpatient numbers.

Figure 2. Pennsylvania hospital regions (Source: Pennsylvania Health Care Cost Containment Council, 2022, https://www.phc4.org/services/datarequests/regionalmap.htm)

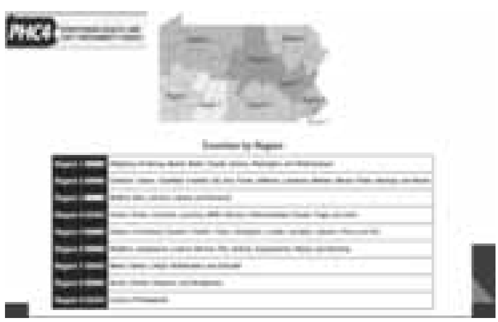


Table 2 shows Pennsylvania hospital characteristics from 2003 and 2018. Table 2 allows to clearly recognize that, across all hospital categories, many of the hospitals either closed or merged by 2018. Maintaining consistency in hospital names throughout the study period was a major challenge; however, the authors took sufficient care during the data wrangling process to ensure integrity of hospital names throughout the study period. Institutional Review Board review and approval were not needed, since the data sources are public.

Table 2. Structural characteristics of Pennsylvania hospitals for 2003 and 2018

Hospital characteristics		Number of hospitals	
		2003	2018
Ownership	For-profit	23	23
	Not-for-profit	150	126
Teaching status	Teaching	38	31
	Nonteaching	135	118
Location	Urban	102	85
	Rural	71	64

In this research, mortality index and readmission index had missing data (3.63% and 4.89%, respectively), and the researchers used regression imputation to account for missing data. A hospital appearing in their dataset for one year is called a hospital-year. For instance, the Abington Memorial Hospital appears in their dataset for 16 years, which is considered as 16 hospital-years. After imputation, there were a total of 2,519 hospital-year observations.

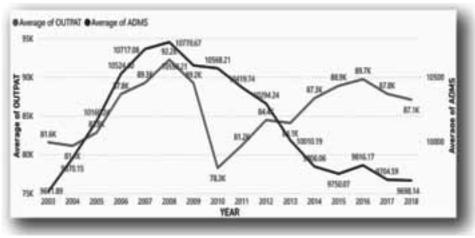
Multicollinearity is a common problem when estimating regression models, which may lead to unreliable and unstable estimates of the regression coefficients. The variance inflation factor values computed for each in response variable ranged from 1.032 to 7.557, which are less than 10, indicating absence of serious multicollinearity effects in the authors' final cross-sectional and serial association (SCC) model (Chatterjee et al., 2000). The correlation matrix in Table 3 determines that no significant violations occur in multicollinearity.

Table 3. Correlation coefficient matrix

	HHI	PCTO65	POPPSM	PCPINC	OPMAR	BDCC	MCNPR	MANPR	REINDEX	MORINDEX	CASEMIX	BEDSSS	ADMS	AVGLOS	ORATE	RNSPBED	OUTPAT
HHI	1.000																
PCTO65	0.084	1.000															
POPPSM	-0.023	-0.544	1.000														
PCPINC	0.030	-0.171	0.065	1.000													
OPMAR	0.029	-0.092	-0.073	0.088	1.000												
BDCC	-0.013	-0.029	0.065	-0.076	-0.055	1.000											
MCNPR	-0.017	0.358	-0.110	-0.117	-0.224	-0.038	1.000										
MANPR	-0.037	-0.124	0.438	-0.015	-0.143	0.355	-0.142	1.000									
REINDEX	-0.016	-0.253	0.321	0.218	0.218	-0.182	-0.080	0.064	1.000								
MORINDEX	-0.022	-0.150	0.127	-0.027	0.187	-0.206	-0.053	-0.058	0.761	1.000							
CASEMIX	0.025	-0.249	0.329	0.208	0.225	-0.237	-0.281	0.042	0.600	0.508	1.000						
BEDSSS	-0.029	-0.271	0.322	0.155	0.183	-0.189	-0.220	0.094	0.839	0.718	0.724	1.000					
ADMS	-0.026	-0.306	0.318	0.169	0.227	-0.194	-0.237	0.057	0.876	0.748	0.716	0.975	1.000				
AVGLOS	-0.072	-0.125	0.329	0.032	-0.020	0.090	0.070	0.257	0.261	0.227	0.276	0.377	0.321	1.000			
ORATE	-0.012	-0.346	0.334	0.132	0.230	-0.092	-0.028	0.052	0.622	0.538	0.439	0.512	0.610	0.419	1.000		
RNSPBED	0.002	-0.235	0.308	0.146	0.198	-0.168	-0.271	0.082	0.770	0.653	0.727	0.948	0.933	0.350	0.500	1.000	
OUTPAT	-0.011	-0.237	0.166	0.151	0.274	-0.175	-0.227	-0.048	0.787	0.690	0.617	0.815	0.858	0.186	0.533	0.790	1.000

Next, the authors plotted the data to observe Pennsylvania hospitals' inpatient admission trend (Figure 3). It was interesting to see that there was a noticeably sharp and significant decline of inpatient Admissions from 2008 to 2018; this means that the sampled data are closely representative of the national trend during this period, as stated in the literature.

Figure 3. Average inpatient admissions and average outpatient admissions in Pennsylvania hospitals from 2003-2018 (Note: COVID-19 was not reported during this time)



Further, the researchers plotted the average NPR, average operating margins, and the total number of hospital closures (Figure 4). As the authors anticipated, there was a clear decline in the average operating margins for Pennsylvania hospitals during the recent period, which was an obvious downtrend beginning 2012. It was remarkable to observe that the average NPR was a gradual uptrend during the entire period from 2003 to 2018. The number of hospitals closed was gradually decreasing, which explains the increasing medical costs in recent years in order to overcome the decline in operating margins.

Figure 4. Average net patient revenue, average operating margins, and the total number of hospitals closed in Pennsylvania in the period 2003-2018 (Note: COVID-19 was not reported during this period)

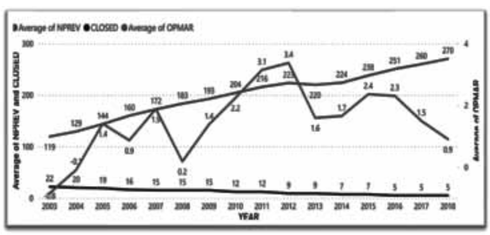


Figure 5 shows the average readmission index and the average population per square mile for Pennsylvania hospitals from 2003 to 2018. Readmission index was in an overall uptrend, while population per square mile was showing a clear declining trend.

Figure 5. Average readmission index and average population per square mile in Pennsylvania hospitals 2003-2018 (Note: COVID-19 was not reported during this period)

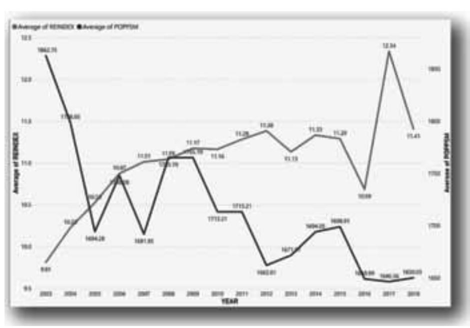
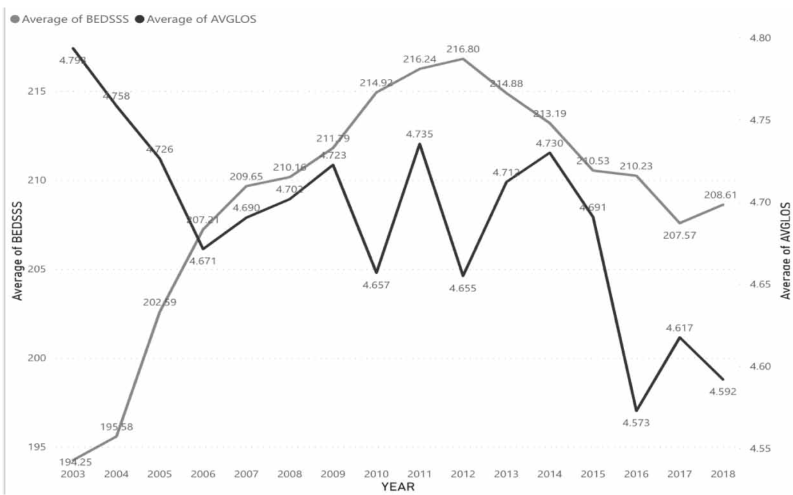


Figure 5 illustrates the average number beds setup, staffed, and supported, i.e. readily available for use by patients, and the average length of change at the end of the cost reporting periods. A bed means an adult bed, pediatric bed, birthing room, or newborn bed in a patient care area for lodging patients in acute, long term or domiciliary areas of the hospital. Figure 6 is a clear indication that the overall trend for both the average number of days patients spent inside the hospital as well as the number of beds setup, staffed and supported follow each other from 2006 to 2018. Overall decline in both measures since 2012 is noticeable.

Figure 6. Average beds setup, staffed and supported, and average length of stay for Pennsylvania hospitals in the period 2003-2018 (Note: COVID-19 was not reported during this period)



It is interesting to investigate whether any of these measures will result in a significant association with the inpatient admissions in Pennsylvania using regression analysis. Before proceeding, the authors also checked for the conditions for regression analysis:

1. The regression function must be linear, that is, the mean Y value at each set of values of the predictors (the X variables) should be a linear function of the predictors.
2. The residuals (errors) should be independent.
3. The residuals (errors) at each set of values of the predictors should be normally distributed.
4. The residuals (errors) at each set of values of the predictors should have constant variance.
5. According to Jaggia et al. (2021), there should not be outliers that significantly impact the model. The authors completed this by analyzing the residuals vs. fitted, normal Q-Q and scale-location plots generated in R studio.

None of the checks showed departures from the above conditions, except the outliers. Therefore, the authors further tested for the effect of influential observations on their estimates. As Bhattarai and OptumHealth (2013) mentioned, there is not a single approach of outlier removal that works for every situation. The authors specifically analyzed the influence, which can be thought of as the product of leverage and outliers. Cook's distance (D_i) is a good measure to determine the influence of an observation. D_i values near or larger than 1 are good indications of influential observations. In the authors' dataset, Cook's distance (D_i) had a maximum value of 0.062, indicating very little influence. A general rule of thumb, however, is that any point with a Cook's distance over 4/n (where n is the total number of data points) is considered as an outlier. Several observations in the dataset exceeded the 4/n threshold, so the authors reran all their regression models without the outliers; the results excluded those extreme values.

Data Analysis and Results

Pooled Ordinary Least Squares and Fixed Effects Model Results

The authors performed all data cleansing, statistical analysis, and regression analysis operations using the software RStudio, while they generated the charts for the manuscript using PowerBI. If there is unobserved heterogeneity correlated with some observed variables, then POLS is found to be inconsistent, whereas FE is consistent. However, FE models have higher standard errors because they estimate only within-hospital differences, disregarding any information about difference between hospitals. An alternative approach is RE models which have smaller standard errors. However, there is always a trade-off between the omitted variable bias in RE models and the efficiency loss due to larger standard errors in the FE models (Allison, 2009). Given these trade-offs, the researchers ran Hausman test to decide between the two models. The null hypothesis was that FE and RE do not differ substantially, and the alternative hypothesis was that RE is not appropriate because random error terms are probably correlated with one or more regressors. The test was statistically significant ($\chi^2 = 415.71$, df = 16, $p<0.001$); therefore, the researchers proceeded with their analysis using the FE model.

Table 4 presents the POLS regression and the FE model results. While the POLS regression resulted in an R^2 of 98.1%, the FE model adjusted for variability in the location, structure, and teaching status, and the applicability of affordable care act could explain 56.4% of inpatient admissions. The authors observed that seven explanatory variables (i.e., beds setup, staffed and supported, average length of stay, occupancy rate, readmission index, registered nurses per bed, Medicare percentage of NPR, and outpatients) became significant in both models. While five out of these seven variables showed positive correlations, average length of stay ($p<0.001$) had a substantial negative effect on inpatient admissions. Medicare percentage of NPR resulted in two different effects for the two models, thus the authors ignored it from further inferences.

Table 4. Pooled ordinary least squares vs. fixed effects model results

	POLS		FE	
(Intercept)	-1,019.60			
	(700.15)			
Beds Staffed and Supported	39.50	***	29.15	***
	(0.37)		*(0.86)*	
Average Length of Stay (Days)	-581.43	***	-452.05	***
	(38.68)		*(44.51)*	
Occupancy Rate	62.74	***	65.88	***
	(3.07)		*(3.49)*	
Casemix Index	-147.10		-63.82	
	(169.27)		*(263.87)*	
Structure (For-profit = 1)	511.77	***		
	(90.73)			
Teaching Status (Yes = 1)	479.10	***		
	(83.08)			

Table 4 continued on next page

Table 4 continued

	POLS		FE	
Location (Urban = 1)	-197.75	*		
	(94.97)			
	(77.87)			
Readmission Index	96.72	***	121.67	***
	(7.70)		*(9.05)*	
Mortality Index	20.36		56.36	*
	(29.30)		*(25.10)*	
Registered Nurses per Bed	597.31	***	223.52	**
	(67.66)		*(73.98)*	
Medicaid % of NPR	-14.65	***	-5.23	
	(4.26)		*(4.64)*	
Medicare % of NPR	-12.48	**	23.30	***
	(4.52)		*(6.72)*	
Bad Debt and Charity Care	39.18		21.94	
	(23.59)		*(27.78)*	
Outpatients	0.01	***	0.01	***
	(0.00)		*(0.00)*	
% Population over 65 years	15.85		83.13	*
	(19.42)		*(33.50)*	
Population per Square Mile	-0.04		-1.22	*
	(0.05)		*(0.61)*	
Per Capita Income	0.01		0.01	**
	(0.00)		*(0.00)*	
Operating Margins	3.22		4.31	
	(3.22)		*(2.80)*	
Herfindahl Index	-928.13		121.64	
	(636.46)		*(481.60)*	
Region Dummies	Included		-	
R^2	0.981		0.601	
Adjusted R^2	0.981		0.564	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Model Robustness, Cross-Sectional Dependency, and Serial Association

With panel data, the presence of serial association, nonstationarity heteroscedasticity (Granger & Newbold, 1974; Maddala & Wu, 1999), and cross-section dependence (Wooldridge, 2010) may lead to loss of efficiency and impede reliable inference of the authors' estimates. They performed robustness tests to check for the presence of these characteristics. The Breusch-Godfrey test as well as Wooldridge test for serial association indicated the authors' FE model suffered from serial association in error term ($\chi^2 = 568.09$, $p < 0.001$). The Breusch-Pagan test for heteroscedasticity confirmed heteroskedastic errors (BP = 253.49, df = 20, $p < 0.001$). Since they were interested in correcting for both serial association and heteroskedasticity, they obtained clustered standard errors, or heteroskedasticity and autocorrelation consistent standard errors, using the "Arellano" method (Arellano, 1987). They also ran the Pesaran cross-sectional dependence (CD) test to check for spatial dependence in their model. Pesaran CD test ($Z = 4.212$, $p < 0.001$) confirmed the presence of CD in the model. There are two general approaches for correcting CDs, namely panel-corrected standard errors and the SCC. However, according to Beck and Katz (1995), the results of the panel-corrected standard errors approach are sensitive to the ratio between T (year) and N (hospitals). The authors used the SCC model as it corrects for heteroskedasticity and serial association consistent errors while, simultaneously, it becomes robust against CD (Driscoll & Kraay, 1998).

Table 5. Fixed effects vs. Cross-sectional and serial association model results

	FE		SCC	
Beds Staffed and Supported	29.15	***	32.93	***
	(0.86)		*(1.56)*	
Average Length of Stay (Days)	-452.05	***	-571.33	***
	(44.51)		*(73.45)*	
Occupancy Rate	65.88	***	67.93	***
	(3.49)		*(5.56)*	
Casemix Index	-63.82		-341.68	
	(263.87)		*(379.65)*	
Readmission Index	121.67	**	98.73	***
	(9.05)		*(15.95)*	
Mortality Index	56.36		80.18	**
	(25.10)		*(28.23)*	
Registered Nurses per Bed	223.52		125.93	
	(73.98)		*(88.24)*	
Medicaid % of NPR	-5.23		-3.94	
	(4.64)		*(4.32)*	
Medicare % of NPR	23.30	*	9.34	
	(6.72)		*(7.46)*	
Bad Debt and Charity Care	21.94		31.21	
	(27.78)		*(25.41)*	
Outpatients	0.01	*	0.01	***
	(0.00)		*(0.00)*	
% Population over 65 years	83.13		42.83	
	(33.50)		*(45.63)*	
Population per Square Mile	-1.22		-0.46	
	(0.61)		*(0.57)*	

Table 5 continued on next page

Table 5 continued

	FE		SCC	
Per Capita Income	0.01	**	0.01	*
	(0.00)		*(0.00)*	
Operating Margins	4.31		0.52	
	(2.80)		*(3.44)*	
Herfindahl-Hirschman Index	121.64		67.25	
	(481.60)		*(313.58)*	
R^2	0.601		0.7743	
Adjusted R^2	0.564		0.7519	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 5 reports the standardized regression coefficients for FE and SCC models. The model fit in the final SCC model was significant and had improved up to 75.19%. It was therefore capable of explaining more than 75% inpatient admissions. Beds set up and staffed, average length of stay (days), occupancy rate, readmission index, outpatients, mortality index, and per capita income became statistically significant in both models. Average length of stay was the only negatively associated factor, while all other six significant variables were positively associated with inpatient admissions.

No Free Lunch Theorem, Significant Variables, and Comparison of Regression Effects With the Preferred Effects of an Ideal State of Healthcare Service Performance

According to Salles Melo Lima et al. (2021), it is very well established in literature that no algorithm is universally better than others across all domains and data sets. These authors further mention that this is also known as the NFL theorem by Wolpert and Macready (2005). According to them, any two algorithms are equivalent when their performance is averaged across all possible problems. Thus, there is no universally best algorithm, and matching algorithms to problems gives higher average performance than does applying a fixed algorithm to all. While the authors limited the findings and recommendations to the domain of this research, they selected the explanatory independent variables that repeatedly emerged as significant across all regression models they used in the research as the significant dominant variables (hereafter referred to as the “factors”) associated with Pennsylvania hospital’s inpatient admissions. The authors found the five independent explanatory variables to be significantly associated with the inpatient admissions across all three best regression models they used in this research. The five independent explanatory variables were: Beds setup and staffed, average length of stay, occupancy rate, readmission index, and the outpatients. Next, they compared the positive or negative effects of those factors on the dependent variable with the “preferred” effects of an imaginary ideal state to identify potential performance gaps in hospital services they considered in the study. At the end, further inferences on such gaps led to the discussion and the recommendations of this research.

The following section presents a detailed discussion of the results to identify preferred levels of services in an ideal state of healthcare services. Next, the section identifies deviations via comparison of current regression effects against the preferred, and finally it provides improvement recommendations.

DISCUSSION

Beds Set Up Staffed and Supported, Occupancy Rate, Readmission Index

The preferred effects of these variables are straightforward. According to the final SCC regression model, if all other variables are kept unchanged, having one more staffed and setup bed can increase the inpatient admissions by 32.33 patients, which is a positive association. More beds staffed and setup is an indicator of the service capacity. A negative association with the inpatient admissions would mean that inpatient admissions would decrease even with more prepared beds, symbolizing an inefficient use of hospital resources. Therefore, positive association between the two indicators is what is ideal and preferred, and the results indicate that Pennsylvania hospitals had being using hospital resources efficiently during the period considered.

The occupancy rate is a calculation used to show the actual utilization of an inpatient health facility for a given period, and a higher rate reflects the efficient use of hospital resources. According to the SCC model results in Table 6, a unit rate increase in occupancy rate will increase the inpatients by 67.93, given the other variables are kept unchanged. While the patient perspective typically is "lesser the crowd, the better," the typical hospital perspective is to maintain higher utilizations without hindering the quality of the services. As per service design and operations management, there is an ideal rate that is best for inpatient services. As Palvannan and Teow (2012) explained, the patient waits longer as the system gets busier, and an increase from 80% to 90% has a larger impact on patient wait time than an increase from 70% to 80%. Thus, the ideal occupancy rate to be maintained in an ADMS service facility should be between 70% to 80% (Jacobs, Chase, & Lummus, 2014; Palvannan & Teow, 2012). This leads to the interpretation that increasing occupancy rates, ideally between 70% to 80%, should be positively correlated to increasing inpatient admissions. Therefore, the positive association between occupancy rate and inpatient admissions reflect an efficient healthcare service Pennsylvanian hospitals provided during the period 2003-2018.

When it comes to readmissions, a higher readmission index signals patients are receiving substandard care and the providers are overlooking complications. Therefore, lower readmissions should be the goal. In the SCC model results, the fact that all other variables are kept unchanged and the readmission index is increased by one unit will cause an increase in inpatients by 98.73. Assuming a reasonable patient concerned on the quality of healthcare service would expect lower readmission rates, a negative association between readmission index and inpatient admissions are preferred.

Therefore, the research results indicate that readmissions into Pennsylvania hospitals during this period were having an unhealthy association with the inpatient admissions, and this finding requires much attention. The conclusion section provides further information on this matter.

Average Length of Stay (Days)

Wang and Zelenyuk (2021), among 265 measures abstracted from the 172 reviewed articles, also identified that the length of stay was one of the commonly used indicators of healthcare provider performance. It is logical that, when a patient occupies a bed for a longer duration, the admission counts go down since another patient cannot be assigned to the same bed. Authors further mention that the opinion surveys done with patients have identified that they do not prefer to stay longer in the hospitals mainly because of the increase in costs. According to Tikkanen (2017), America had fewer physician visits than peer industrialized countries in recent years prior to COVID-19; this could be related to the increasing healthcare costs. The inflation-adjusted mean cost per stay indeed increased by 12.7% overall from 2005 to 2014. Further, the inflation-adjusted cost per stay for patients covered by private insurance or Medicaid increased by 16% to 18%, while the cost per stay for Medicare-covered patients and the uninsured changed minimally (McDermott et al., 2017). These statistics indicate a potential effect of cost on the association between the average length of stay and the inpatient admissions. Shorter days in care is believed to reflect effective and efficient healthcare services which result in faster patient recovery. This is the service level both the caregivers and the receivers prefer. An ideal facility with such a performance index should be able to attract more inpatients due to its good reputation for service. Hence, the ideal effect of the average length of stay on the inpatient admissions should be a negative relationship. As per the SCC model results, it is a negative relationship where an increase of the average length of stay by one day, while keeping other variables fixed, causes a decrease in inpatients by 571.33. Thus, the average length of stay does not indicate any performance lacks during the period the authors considered for this study. However, newer technologies healthcare facilities use, such as new orthopedic technologies, are contributing more towards reducing the time patients spend in the hospital (Kelly, 2022).

Outpatients

Secondary research studies reveal that many consider the decrease of inpatient admission numbers is caused by the impact of the increasing number of outpatient admissions. In fact, this phenomenon is true to Pennsylvania during the time of this study, especially after 2010 (Figure 2). Outpatient care in hospitals improved significantly in more recent years, even prior to the pandemic, with added artificial intelligent and information technology-based services. Two excellent examples of the advancement in the health service sector are the computerized triage system and telehealth services.

The “triage” is a process for prioritizing the allocation of limited resources when the demand for resources exceeds their availability (Aronsky et al., 2008). Since overcrowding of emergency departments is a universal and ever-increasing problem, most emergency departments have a triage system in place to facilitate the prioritization of patients (Zachariasse et al., 2019). Telehealth has many synonymous terms depending on the context of application, few being the telecare, telemedicine, teledermatology, teleradiology, e-health, and Teladoc services.

Telehealth [is] a method to deliver healthcare services face-to-face via telemedicine technology to facilitate the diagnosis, monitoring, consultation, treatment, education, care management and self-management of a patient’s healthcare while the patient is at an originating site and the healthcare practitioner is at a distant site. Telemedicine [is] the delivery of healthcare services face-to-face using interactive telecommunication technology during the actual time when such services are being provided to facilitate the assessment, diagnosis, monitoring, consultation, treatment, education, care management and self-management of a patient’s healthcare while the patient is at an originating site and the healthcare practitioner is at a distant site. The term does not include standard telephone conversations, facsimile transmissions, and email. The interactive telecommunication shall include, at a minimum, audio, and video equipment (Pennsylvania Department of Health, 2016, p. 1).

An example would be how technology has acted as a great enabler of patient continuity through remote consultation, ongoing monitoring, and patient education using telephone and videoconferencing, and the use of text messaging as a model for service delivery (Hall, 2015; Park et al., 2014). Likewise, a simple service such as text messaging has proven efficacious in diabetes self-management, smoking cessation, weight loss, physical activity, and adherence to medication regimens such as in human immunodeficiency virus infection and acquired immune deficiency syndrome (i.e., HIV/AIDS) patients who are on antiretroviral therapy. Several studies have found that home-based telemedicine programs reduce care costs (Michaud et al., 2018; Sayani et al., 2019). Some studies have found telemedicine to be economically beneficial not only by reducing the socioeconomic barriers to cost and access, but also by increasing the uptake of services (Sayani et al., 2019).

The shortage of physicians in the USA coupled with the associated increased healthcare service costs, the decreased face time with the physicians, against quick, convenient, and cheaper and quicker medical advice make these novel systems more appealing to patients than obtaining health services as inpatients (Kichloo et al., 2020; Michaud et al., 2018). According to LaPointe (2019), outpatients have become popular because of the lower costs associated with outpatient care. As LaPointe explained, the outpatient care is not subject to hospital room charges or other related fees, making outpatient substantially less expensive than inpatient care. LaPointe further mentioned that the average inpatient stay cost over $22,000 in 2016, while outpatient costs averaged about almost $500. Further findings include more convenient recovery as a top advantage of outpatient care, since patients can recover at home while receiving the same quality of care as in a hospital (LaPointe, 2019). The Deloitte Center for Health Solutions' recent research further validates this finding. Their article stated that the increase in the volume and scope of outpatient services were due to the advances in clinical technology, growing pressure by payers to adopt value-based payment models that incentivize treating patients in lower-cost settings (where appropriate), and the consumer's desire to avoid hospitals (Gerhardt & Arora, 2020). According to Weiss & Jiang (2021), several factors have recently contributed heavily:

1. Medicare's two-midnight rule and observation status require that certain patients who previously would have been admitted to the hospital and billed for inpatient services are now admitted to the hospital under observation status with outpatient billing.
2. Consumers have an increasing preference for outpatient settings due to their greater convenience and lower out-of-pocket costs.
3. Medicare, Medicaid, and commercial plans are pressuring health systems to take on value-based contracts, which aim to shift care away from inpatient settings.
4. Hospitals are acquiring physician practices to support their position in the market, including their ability to deliver on value-based contracts. Physicians are reimbursed at a higher rate if they bill as hospital-based outpatient departments vs. freestanding outpatient clinics (Weiss & Jiang, 2021).

Figure 3 which was presented previously shows the outpatient trends over the period from 2003 to 2018 in Pennsylvania hospitals where an overall increase in the number of outpatients occurred over the years. The preferred effect of outpatient admissions on the inpatient admissions should be more of a symbiotic and/or complimentary relationship, rather than competitive. More of the inefficiently utilized resources tied up with inpatient care needs to be released and reallocated or shared with the outpatient care to ensure a productive service in hospitals. As the authors mentioned previously, a considerable percentage of outpatients gets hospitalized on medical advice, thus the ADMS numbers increase, especially from the ER visits. For instance, in 2018, there were over 143 million ER visits, and, of these, more than 20 million ended in admission to the same hospital. However, what would be ideal for a healthier society would be for patients to get adequately treated at the outpatient services, so that there is no need for them to be admitted as inpatients. Therefore, the ideal and preferred association and the effect for outpatients on the inpatient admissions should be a significant negative association. According to the final regression model results, currently it is a significant positive effect on inpatient admissions. If all other variables are kept fixed, every 100 outpatients will cause an increase in the inpatients by one more. The results indicate a shift towards the ideal; the authors discuss this further in the conclusion section.

In brief, for Pennsylvania hospitals during the period 2003-2008, the outpatient admissions and the readmission index indicated deviations from the preferred performance levels of an ideal state. The beds setup, staffed and supported, average length of stay, and occupancy rate factors resulted at satisfactory performance levels. Table 6 presents these significant factors and the comparison of regression results with the ideal or preferred results. Out of the five factors, readmission index and the outpatient admissions show deviations from the preferred service level of an ideal state.

Table 6. Current regression effects vs. Preferred effects in an ideal state

Significant Factors	Regression Effect on Inpatient Admissions	
	Current Effect	Preferred Effect
Beds set up and staffed, BEDSSS	+	+
Average Length of Stay, AVGLOS	-	-
Occupancy Rate, ORATE	+	+
Readmission Index, REINDEX	+	-
Outpatients, OUTPAT	+	-

The following section presents a further discussion on the outpatient admissions and readmissions, recommendations, research limitations, and the future research directions based on the findings of this research.

CONCLUSION

It is very clear that identifying factors associated with inpatient admissions is important for managing healthcare services efficiently. The objective of this research was to demonstrate a systematic methodology using regression analysis to identify the most significant factors associated with non-COVID-19 inpatient admissions, as well as to identify which of them have considerably deviated from an ideal service state. To achieve this objective, the authors initially used the RE regression, POLS regression, and FE regression models on Pennsylvania, USA, hospital data during the period 2003-2018 to ensure non-COVID-19 illnesses. After comprehensive statistical analysis and the use of NFL theorem, the authors identified five factors associated with inpatient admissions that appeared significant across all regression models they used. Then, they compared the resulting significant regression effects with the preferred healthcare service performance levels of an imaginary ideal state of healthcare performance. Accordingly, they provided recommendations pertaining to the scope of the research.

It is interesting to find readmission and outpatient care have become two hot topics in present healthcare literature, further validating the findings of the authors' research. According to Weiss and Jiang (2021), hospital readmissions are a leading healthcare concern, both in terms of implications for the quality of care provided to hospitalized patients and for the healthcare costs associated with readmission. In 2018 alone, there were a total of 3.8 million adult hospital readmissions within 30 days, with an average readmission rate of 14% and an average readmission cost of $15,200 (Weiss & Jiang, 2021). Preventing avoidable readmissions has the potential to profoundly improve both the quality of life for patients and the financial wellbeing of health care systems. According to Alper et al. (2022), avoidable readmissions are difficult to define and may be related to therapeutic errors and failed handoffs. However, identifying patients at increased risk for post-discharge adverse events and readmission, as well as identifying systemic issues which contribute to failed discharge transitions are crucial. It will help make intelligible decisions to improve the quality and the safety of the discharge process for all patients. Further, their article presents an overview of the discharge process, determination of the appropriate next site of care, and review of interventions to reduce the likelihood of unplanned readmissions and adverse events after discharges. They also refer to an interesting classification as predischarge interventions (i.e., patient education, discharge planning, medication reconciliation, and scheduling a follow-up appointment), postdischarge interventions (i.e., follow-up phone call, communication with ambulatory provider, and home visits), and bridging interventions (i.e., transition coaches, patient-centered discharge instructions, clinician continuity between inpatient, and outpatient settings). While many readmission reduction programs can be found across the healthcare facilities in the USA, there is significant variability in the availability of services and types of facilities across geographic areas. Therefore, the success varies much.

Outpatient healthcare services have shifted their paradigm with the novel technology and have attracted more outpatients, in recent times. Findings of a Deloitte Center for Health Solutions' (Gerhardt & Arora, 2020) research, which included hospital financial data analysis and interviews with 20 health system executives across U.S. hospitals, revealed that, between 2011 and 2018, hospital outpatient revenue grew at a higher compounded annual rate (9%), compared to inpatient revenue (6%), and that the aggregate outpatients' share of total hospital revenue grew from 28% in 1994 to 48% in 2018. The shift toward outpatient will likely have a tremendous impact on operations, business models, staffing, and capital. Thus, health systems should plan not only about how to manage their traditional business model, but also on new competing business models to avoid themselves struggling (Weiss & Jiang, 2021). Instead of focusing on capturing more hospital inpatients, health systems should start planning for a future where buildings full of beds will likely be a memory (Weiss & Jiang, 2021). Several other studies validate the anticipation that the trend will continue after the pandemic. According to Moody's investors service data, before COVID-19, hospital admission rates were already trending flat, and outpatient revenues consistently outpaced inpatient revenues (Kelly, 2022).

The literature presents strategies for those intentionally growing their organizations' capacity in outpatient and home settings as volume strategies and population health strategies. Hospital systems following volume strategies are confident on brick-and-mortar clinics and are investing in urgent care centers, ambulatory surgery centers, imaging centers, and primary care clinics to broaden access for their consumers (Gerhardt & Arora, 2020). Population health strategies, on the other hand, are to rely less on inpatient revenue by investing in remote monitoring and other forms of virtual health, building, or buying clinics and hiring care coordination and other related staff to better coordinate care, treat patients in the lowest cost settings, and improve quality (Gerhardt & Arora, 2020). Moody's investor services note that several providers in the U.S. are focused on expanding in-home acute care admissions (Kelly, 2022). For example, Mayo and Kaiser are among more than a dozen systems that launched the Advanced Care at Home Coalition in October 2021. In May 2021, Mayo Clinic and Kaiser Permanente invested in Medically Home, a service that helps health systems develop complex care-at-home models that would allow some providers to reduce inpatient beds, while others, such as academic centers, increase inpatient capacity as needed (Kelly, 2022). Several other factors which contribute to the increase in outpatient services in the U.S. are: Reimbursement changes and risk-sharing models; decision by CMS to remove certain orthopedic and cardiac procedures from its inpatient-only list, since it helps drive more treatment to hospital-based outpatient departments or ambulatory surgery; CMS' penalties for excessive readmissions; new drugs and at-home heart monitors (Kelly, 2022). In addition, there is mutual impact of other programs (e.g., the CMS's readmission reduction program—CMS is part of the Department of Health and Human Services). They imposed penalties for excessive readmissions to keep the numbers low, which contributed to the increased number of outpatients (Kelly, 2022).

Additionally, the authors recommend examining the potential benefits of sharing resources between inpatient and outpatient services on need basis. Hospitals specialized in certain services, such as the teaching hospitals with a strong focus on highly complex cases requiring greater levels of specialty care, will be better able to sustain demand for inpatient services than hospitals that offer mostly secondary care (Kelly, 2022). Thus, a proper classification methodology to identify existing resource levels and current outputs, preferred resource levels and output levels, and a mapping between the two states will help formulate effective strategies to transform the existing state of healthcare service in the U.S. Finding the perfect balance between how much of inpatient resources vs. outpatient resources is tedious; however, resource sharing is a potential solution.

The authors also recommend increasing the operational agility of healthcare facilities by employing a multiskilled workforce, and flexible schedules where the workers are given the option to choose their work mode (e.g., which days in the inpatient admissions vs. which days in outpatient and telehealth services). Synergetic healthcare system where both private and public sector healthcare providers could work collaboratively to find systematic solutions to resolve current healthcare sector issues is another recommendation. Here, the aim should be to provide higher quality, efficient, and effective value-based care at an affordable cost for all patients. Studying healthcare service models from other countries, operational environments which promotes innovative ideas to help during the transitioning of hospital services is a further recommendation.

The authors' biggest research limitation was the use of Pennsylvania hospital data as opposed to data from a bigger geographical coverage. However, the impact is minimal, since the authors' intention was to use these data to demonstrate how the systematic methodology can be applied to reach the conclusions. Another limitation would be the need to depend on past data to arrive at conclusions. Accordingly, they recommend large and recent datasets for more accurate picture on current performance levels. According to the authors' results, inpatient admissions in Pennsylvania hospitals were declining, while outpatient services were increasing, during the period of their study. Also, the healthcare service areas related to readmissions and outpatient admissions indicated deviations from preferred service levels. The literature provides abundance of evidence to state that the authors' findings appear across U.S. healthcare services. They discussed the impact of declining inpatient admissions, impact related to increasing readmissions, impact of increasing outpatient care, what steps the healthcare systems have already implemented in the U.S., along with additional recommendations to improve healthcare operations. This research can be considered unique for the systematic methodology the authors introduced and the findings. Future research directions include expanding this investigation to other states of the U.S. to identify the generalizability of the results. The simplistic nature of the methodology the authors used and the open-source software make further expanding this research topic easier. The poor health of people is a social challenge that needs to be immediately addressed. Hospital administrations, clinicians, academia, healthcare policy makers, and even the general population may find the insight the authors offered by this paper to be useful in such endeavors.

COMPETING INTERESTS

The authors of this article declare there is no competing interest.

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