An empirical study of ambulatory surgery access in multilevel context

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Abstract

As a fast-growing sector of the healthcare industry, Ambulatory Surgery Centers (ASC) offer timely and cost-saving services in public health. In this study, large-scale data from the American Community Survey and the Office of Statewide Health Planning and Development (OSHPD) are merged to examine factors of ASC access on multiple dimensions. The analytic method conforms to a well-established CIPP paradigm to justify results-based accountability on what works, for whom, and in which context. While identifying significant impact of family income, population density, and early childhood support, this study further reveals a moderate effect of health insurance coverage on ASC access.

Keywords: Posterior Capsule Rupture, Vitrectomy, Cataract Surgery, Best Practice.

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Introduction

Along with rapid development of medical technology, many operative procedures were moved from in-hospital environments to ambulatory service centers (ASC)[1,2]. The Office of Statewide Health Planning and Development (OSHPD) has been collecting patient origin data since 2005 to monitor the changes in ASC access. During the same period, the U.S. Census Bureau conducted the American Community Survey to gather contextual information for local service planning. Sonier and Lukanen [3] recollected that the ACS [American Community Survey] asks about demographic and socioeconomic characteristics, and that a question on current health insurance coverage was added in 2008. The ACS has a response rate of 98% and collects data from about 460,000 Californians in 160,000 households, acquiring the largest sample of any population survey conducted in California or nationally. In this study, the OSHPD data are merged with information from the American Community Survey to examine factors of ASC access in multilevel context.

Literature Review

In the United States, communities have zip code identifications set by the federal government. Rip [4] attested that the zip or postcode is the smallest geographic unit available by which to analyze hospitalization data. Although the code designation has been around for many years, the OSHPD data collection is relatively new and most researchers are unaware of its existence. Consequently, Weber [5] noted that relative to hospitals, much less is known about ASCs, and few trustworthy national statistics are available. As a pilot study, Wang et al [6] employed the OSHPD data to indicate needs for including contextual factors at both county and community levels. Built on that result, an innovative feature of this investigation is to expand the examination of ASC access through articulation of additional information from the American Community Survey.

Population Demand on ASC Access

In the 21st century, over 55% of the U.S. population relies on employment-based healthcare insurance [7]. Consequently, most young children receive healthcare through their parent's insurance plans. Because many young couples split up after just a few years, divorce issues have often compromised healthcare coverage for newborns. In addition, young children are more vulnerable to inadvertent injuries. Charoo [9] acknowledged that the freestanding ASC environment is less stressful since patients do not feel like they are being admitted to the hospital, which is especially beneficial to the pediatric patient population. To address the population needs, California voters passed Proposition 10 in 1998 to designate child health as a focus area for Children and Families Commissions across 58 counties [10] with state revenue collected from a $.50 per pack tax on tobacco products to fund services for children ages 0–5 and their families.

To ensure equity of the state revenue distribution, Proposition 10 stipulates the designation of more funding to densely populated counties that have a higher birth rate [11]. Therefore, the state investment varies across urban and rural areas. Through incorporation of the large scale data from the American Community Survey, this study is well-positioned to disentangle profound factors of ASC access across the dimensions of population density, insurance supports, and the Proposition 10 impact.

The CIPP Paradigm

While featuring exploratory inquiries in data analyses, this investigation is also grounded on a theoretical framework to enhance the confirmatory aspect of research design. According to Hedges and Rhodes [12], the randomized experiment is the only method known that can yield **model-free** unbiased estimates of causal effects. Alternatively, multilevel analyses depend on the model selection, as pointed out by O'Connell and McCoach [13].

One useful approach to evaluating healthcare service is known as the *Context, Input, Process, Product* (CIPP) model [14]. According to

Valentine [15], the CIPP framework provided a useful organizational scheme for caring and its multiple interrelationships with other components of the health care setting. In this study, factor selection is guided by the CIPP model to support the large scale data analyses.

Ambulatory surgery has been defined as an organized process whereby patients have surgery, recover and are discharged home the same day. This time constraint has made ASC access more germane to residents in local *context*. Based on justification of population demand in the previous section, *population density* is included to describe variability of ASC access across different communities.

The *input* resources are represented by *median income per family*, as well as the funding support from Proposition 10. In Kern County alone, Proposition 10 has channeled over $160 million to enhance child health and development in the past 15 years [16]. Across the state, the American Community Survey incorporated the ongoing collection of community data to represent proportions of the local population under age 6, which were suitable for examining the sustainable impact of Proposition 10. Brady [17] noted that the CIPP model is particularly useful when the product is long-term and sustainable.

In the decision-making *process*, insurance support is particularly helpful to low-income families [18]. Vogt and Romley [19] concurred that in general, ASCs tend to serve a higher-income and more-generously-insured population. While married couples typically had higher incomes [20], father-only groups were in better economic standing than mother-only groups [21]. Unfortunately, more mother-only family groups had young children, under the age of 6, in the household as opposed to father-only family groups [21]. Hence, the supporting platform should also be considered when examining ASC access.

In the *product* phase, the OSHPD data were analyzed to examine the difference in ASC access across various counties and communities. Morrissey [22] reported that for every additional ASC per 100,000 people in a population, a reduction of 4.2% in hospital outpatient surgeries will result. The shift in the healthcare industry has generated strong interests in analyzing ASC access under multilevel contexts [23].

In summary, research literature suggests that the CIPP model is a holistic approach to conducting evaluations of education, health, and other public programs [24]. Through incorporation of the CIPP platform, Table 1 is developed to summarize variable selections for this investigation. Sloane [25] characterized the multilevel approach as a paradigm improvement, stating, "We change the basic research question from what works to what works for whom and in what contexts".

Table 1 Multilevel Variables from OSHPD and ACS Databases

Variable	Level	Data Source
Dependent variable		
Outcome of Ambulatory Service Access	Community*	OSHPD
Independent variables		
Proportion of the population with insurance coverage	County	Census Bureau
Population density	Community	Census Bureau
Median family income	Community	Census Bureau
Proportion of families with children under age 6	Community	Census Bureau

*Community is identified by the ZCTA code from U.S. Census Bureau.

Research Questions

Research questions that guide this investigation are:

(1) What multilevel factors demonstrate profound contributions to ASC access?

(2) How do the results of multilevel modelling fit the empirical data from OSHPD and the American Community Survey?

While the analysis of ASC access leads to identification of significant factors at multiple levels (Question 1), Goldstein [26] cautioned that "These multilevel models are as good as the data they fit; they are powerful tools, not universal panaceas". Hence, Question 2 is developed to confirm the model fit to the multilevel database.

Methods

O'Connell and Reed [27] noted that the goal of multilevel analysis is to attempt to explain variability, which implies that the outcome of interest can be reliably modeled through a well-chosen or predefined set of predictors, covariates, or explanatory variables. Based on variable identification in Table 1, the Hierarchical Linear Model software is employed to conduct multilevel analyses of ASC access in Question 1.

Improvement of the model fit is assessed through a comparison with a null model prior to the introduction of multilevel factors. Garson [28] pointed out that the null model serves two purposes: (1) It is the basis for calculating the intraclass correlation coefficient (ICC), which is the usual test of whether multilevel modeling is needed; and (2) it outputs the deviance statistic (-2LL) and other coefficients used as a baseline for comparing later, more complex models. Therefore, ICC, -2LL, and additional model-fit indices are computed to examine the data support for multilevel modeling (Question 2).

Results

Due to the time required for data processing, the 2012 OSHPD data was released in 2014. This study is grounded on the same data from Wang et al6 to partition variability of ASC access using the OSHPD data from 1,746 communities across California. The new results reconfirmed significant variations of ASC access at both county ($Z=4.07$, $p<.0001$) and community ($Z=35.27$, $p<.0001$) levels. An ICC value of .11 from these authors also supported needs for incorporating multilevel explanatory factors.

Descriptive Findings

One further step in this study is to merge data between OSHPD and the American Community Survey. Descriptive statistics are computed for variables of the CIPP model in Table 2. At the community level, the annual ASC access in each community ranges from zero to 108, resulting in a standard deviation (SD) of 24.92. Because of different scales for measuring predictors at both community and county levels, a recommendation of Quinn and Keough [29] is adopted to standardize variables in Table 2.

Results in Table 2 further indicate a significant correlation between the median family income (X3) and the percent of families with children under the age of 6 (X3). However, strength of the correlation is weak ($r=.12$). Similarly, other correlation coefficients in Table 2 are very small, indicating a minimal co-linearity issue among predictors.

Table 2 Descriptive Statistics for OSHPD and ACS Variables.

Variable	Mean	SD	X	X_2
Dependent variable				
Outcome of Ambulatory Service Access	27.84	24.92		
Independent variables				
Community level				
X_1: Population density (count/square mile)	3185.00	5168.00		
X_2: Percent of families with children under age 6	21.53	41.59	.12*	
X_3: Median family income	72857.00	33939.00	-.03	.01
County level				
X_4: Health insurance coverage (%)	85.59	3.74		

*p<.0001

Multilevel Modeling

Built on the CIPP paradigm for variable inclusion, a full model is expressed for the dependent variable of ASC service access (Y_{ij}) in the ith community in the jth county:

$$\text{Level-1:} Y_{ij} = \beta_{0j} + \beta_{1j} X_1 + \beta_{2j} X2 + \beta_{3j} X_3 + \varepsilon_{ij} \qquad (3)$$

where $\varepsilon_{ij} \sim N(0,\sigma_2)$; X_1, X_2, and X_3 represent factors of family income, population density, and the proportion of families with children under age 6 at the community level, respectively.

At level 2, intercepts (β_{0j}) depend on an overall mean (γ_{00}) adjusted by a moderate factor (X_4) and a random deviation for county j (u_{0j}).

$$\begin{aligned} \text{Level-2: } \beta_{0j} &= \gamma_{00} + \gamma_{01} X_4 + u_{0j} \\ \beta_{1j} &= \gamma_{10} + \gamma_{11} X_4 \\ \beta_{2j} &= \gamma_{20} + \gamma_{21} X_4 \qquad (4) \\ \beta_{3j} &= \gamma_{30} + \gamma_{31} X_4 \end{aligned}$$

where $u_{0j} \sim N(0, \tau_{00})$ and X4 represents the percent of *insurance* coverage at the county level. Because β_{1j}, β_{2j}, and β_{3j} are regression coefficients for fixed factors at Level 1, no random component is introduced at Level 2 except for inclusion of X_4 to reflect the impact of insurance coverage.

Results in Table 3 indicate significant influence on ASC access from family income (X_1), population density (X_2), and the proportion of families with young children (X_3) at the community level (α=.01). While the insurance coverage variable (X_4) is insignificant, interaction effect has been found significant between X_3 and X_4 at α=.05, indicating an inseparable impact of insurance coverage and early childhood service on ASC access. Meanwhile, insurance coverage (X_4) does not show significant interaction with X_1 and X_2, and hence, the impact of insurance coverage remains consistent regardless of population density and family income.

Table 3 also includes effect sizes in the result reporting. Cohen30 defined the threshold of effect size as small, d= .2, medium, d= .5, and large, d= .8. More recently, Bloom and coworkers31 reviewed effect size, and cited Lipsey's work32 to treat d=.15 and d=.45 as the small and medium thresholds for empirical studies. In conclusion, variables at the community level demonstrate a significant impact on ASC access at α=.01 (Table 4). The results also show a near medium impact from healthcare insurance coverage (X_4) at the county level.

Table 3: Statistical Testing of Multilevel Effects.

Source	Fixed Effect	F Test	Effect Size
Community	Family Income (X_1)	F(1, 1431)=10.11, p=.0015	.17
	Population Density (X_2)	F(1, 1431)=66.94, p<.0001	.43
	Proportion of Families with Young Children (X_3)	F(1, 1431)= 7.49, p=.0063	.14
County	Insurance Coverage (X_4)	F(1, 38)=1.81, p=.1860	.44
Interaction	$X_1 * X_4$	F(1, 1431)= 1.55, p=.2140	.07
	$X_2 * X_4$	F(1, 1431)= 1.32, p=.2510	.06
	$X_3 * X_4$	F(1, 1431)= 6.05, p=.0140	.13

Model Fit Indices

In examining the model-fit indices, a likelihood-ratio test was used to compare deviances between a null model and a full model.

Table 4: Comparison of the Model Fit Index.

Model	Deviance	Number of Parameters
Null Model	23104.2	2
Full Model	12539.0	12

Chi-Square Test on Improvement of the Model Fit

$\chi 2 = 23104.2\text{-}12539.0 = 10565.2$
df=10
$p < .0001$

Table 4 illustrates the construction of χ^2 test on improvement of the model-fit index. The result indicates a significant improvement of the full model over the null model [χ^2 (10) = 10565.2, $p < 0.0001$], which supports adoption of the full model.

To reconfirm the necessity for variable inclusion, Roberts [33] further suggested employment of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to include a 'punishment factor' based on the number of parameters estimated. He elaborated that when comparing competing models, one simply needs to consult these statistics to see if the values for each went down from the previous model's estimate. If so, then the new model is considered to be a better model to fit the data than the previous model. With the penalty of AIC and BIC against adding redundant variables, the full model shows smaller values of AIC and BIC while including more variables (Table 5). Therefore, the model-fit indices consistently endorse inclusion of the multilevel variables in this investigation.

Table 5: AIC and BIC Comparison Between the Null and Full Models.

Index	Null Model	Full Model	Difference
AIC	23108.2	12545.0	10553.9
BIC	23112.3	12550.0	10554.7

In summary, the CIPP paradigm from the current research literature demonstrates an effective control of co-linearity among the explanatory variables (Table 2). Results were aggregated for the full model to assess the impact of multilevel factors on ASC access (Table 3). In addition to reconfirming the need for multilevel analyses (Table 4), AIC and BIC indices are presented in Table 5 to show the parsimonious feature of model building, that, according to Kuha [34], provide well-founded and self-contained approaches to model comparison.

Discussion

Although the ASC model has been endorsed by the American Medical Association and the American Society of Anesthesiologists since the early 1970s [35], Cascardo [36] reported that a substantial number of ASCs still fail. While the outcome may reversely impact endorsement of professional organizations, it is more important to proactively examine profound factors behind ASC functioning.

Munnich [37] noted that standardized data on ambulatory surgery centers was difficult to access. Instead of waiting for the data availability, an innovative feature of this investigation is to fill the void through merging large scale data from OSHPD and the American Community Survey. To ensure the rigor of this investigation, the variable selection is guided by a well-established CIPP paradigm from the research literature, and multiple approaches have been employed to confirm the model-fit indices.

In addition to intellectual merits on the methodology front, this study enhances the impact of research findings on multiple dimensions. By nature, ASCs are smaller than hospitals on average [5]. Targeting smaller procedures, ASCs are required to have a transfer agreement with Medicare-certified hospitals when special care is needed for patients with greater co-morbidities [38]. The service delimitation has characterized ASC access in the domain of public health. Therefore, this study reconfirmed population density (X_2) as a significant factor of ASC access. Results in Table 4 show a moderate effect size from population density to indicate its practical importance.

Following the CIPP paradigm, family income is an indicator of the input resource to support ASC access. Plotzke [39] reported that an increase of $1000 in family income decreases the likelihood that the child will be without insurance by as much as 2.8%. Accordingly, this investigation reveals a significant relation between family income and ASC access (Table 4). Furthermore, Doerpinghaus [40] asserted that insurance coverage dampens price variation considerably, making price much less important than it might otherwise have been. With inclusion of the insurance factor, the impact from family income seems to be restrained by additional support from healthcare plans, resulting in a small effect size for the family income variable (X_1) (Table 4).

In history, the first ambulatory surgical procedure in the United States was conducted for a young girl who fell and suffered a penetrating head injury in 1650 [41]. During the process of child growth, infants and toddlers have a fragile body structure, and are inexperienced in self-protection. A significant portion of Proposition 10 funding is devoted to supporting health insurance coverage for children at ages 0–5 [42]. In this study, the health insurance factor (X_4) is measured at the county level. In addition, a variable is included from the American Community Survey to track the proportion of families with children under age 6 (X_3) at the community level. The significant interaction effect of X_3 and X_4 indicates a strong insurance protection in communities with a higher proportion of families raising young children in this age group.

Another feature of the multilevel analysis is derived from the data structure in which multiple communities are nested within each county, causing a much larger sample size at the community level. Coe [43] reviewed this issue of statistical difference, and concluded,

> The main one is that the p-value depends essentially on two things: the size of the effect and the size of the sample. One would get a 'significant' result either if the effect were very big (despite having only a small sample) or if the sample were very big (even if the actual effect size were tiny).

From the process perspective, the number of surgeries in ASCs has increased relative to the number of surgeries in hospitals for all types of insurance coverage categories [37]. In particular, Dyer [44] observed that the increase in outpatient visits is driven in part by a rise in high-deductible health insurance policies with large out-of-pocket payments for non-catastrophic services. Hence, insurance coverage offers general support for ASC access. Although the smaller sample at the county level makes it more difficult to attain statistical significance for X_4, a moderate effect size is obtained to reconfirm the broad impact from health insurance coverage on ASC access (see Table 4).

In summary, this study has addressed two questions through multilevel data analyses. The first question tackled dependency of ASC access on both support resources and population demands. From the resource aspect, health care costs are driving American families into financial collapse [45] and freestanding ASCs are known for their mastery of cost containment [9]. Thus, family income and insurance coverage are important factors to identify the support background for ASC access. In addition, this empirical study has linked ASC access to population needs, suggesting more community demands in densely populated areas with a higher proportion of young children in the population.

O'Connell and McCoach [13] suggested that model selection should be guided by theory and informed by data. Asides from following the theoretical framework articulated by the CIPP paradigm, the full model has stronger data support than a null model without inclusion of the multilevel variables. Improvement of the model-fit outcomes was not only suggested by the $\chi 2$ test result in Table 4, but also reconfirmed by application of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) in Table 5.

Although strengths could have been claimed on both theoretical foundation and empirical support for this investigation, it should be acknowledged that merit of this study is inseparable from the data quality. Locations of ASC access are difficult to document for seasonal farmworkers, especially those who have no zip code affiliation [46]. Proposition 10 pledges support for children ages 0–5 and their families regardless of immigration status; however some parents may choose to avoid public assistance [47]. As additional progress is made by the federal and state governments to resolve these issues in data collection, results of this investigation should be subjected to reconfirmation in future studies.

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