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Data-Informed Decision Support to Improve Pediatric and Maternal Care Quality Under Medicaid Managed Care Settings

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by

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Dedication

To my mother, father, sister, and my beloved wife.

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Abstract

Over the last two decades, the United States has spent almost twice as much per person in healthcare compared to most other wealthy countries. However, this higher spending has not necessarily transformed into improved quality of care; According to World Health Organization reports, the US now ranks 39th for child health and wellbeing and worst in maternal care among developed nations. In terms of proportion of preventable hospital visits, low-risk cesarean sections, and avoidable maternal morbidity/death, the U.S. is among the highest compared with the peer nations. The prevalence of these adverse outcomes in pediatric and obstetric care is particularly disproportionately high among Medicaid beneficiaries in comparison to privately insured patients, mainly driven by persistent disparities in access to care and care experiences. Consequently, Medicaid expenditure for these groups has been straining federal and state budgets in the last decades, and a substantial increase is expected in the future. In the US, nearly half of obstetric and more than a third of pediatric healthcare is provided through the Medicaid program, and the Medicaid system continues to face substantial challenges in improving care quality and reducing cost in what is now a major policy concern. The key challenges in improving the quality of child and maternal health services provided through Medicaid are (1) how to enhance understanding about the causes and implication of pediatric care fragmentation, higher preventable hospital visits and cesarean rates, and (2) how to better design decision support for Medicaid patients that considers all major stakeholders, which can reduce adverse outcomes, improve health in the vulnerable population and consequently, saves money for the American people.

The objectives of this dissertation, therefore, were to generate new knowledge regarding care fragmentation and disparities in pediatric and maternal health and to develop improved, data-informed decision support that aims to reduce the adverse outcomes associated with Medicaid settings. Using the Florida State and national claims databases, fragmentation of pediatric care was explored in the context of index vs non-index readmission, then associated risk factors were identified, and finally impact of this difference in destination effect on readmission outcomes were explored. Furthermore, after illustrating novel geographical and racial disparities in the fragmented context of pediatric care and the adverse implications of non-index readmission, ways of improving pediatric readmission prediction were explored that could aid both managed care programs and hospitals in designing comprehensive interventions that target children who are at high risk for readmission. More specifically, two innovative decision support approaches were proposed to enhance the prediction of pediatric readmission as compared with existing approaches. First, a novel early risk predictive model was proposed at the time of hospital admission that improves the high-risk patient selection process for hospitals. In the second approach, a cohort-specific readmission model was proposed that achieved higher discrimination when compared with traditional all-cause readmission models. In addition, an innovative framework of preventable ED visits and revisit prediction models at three patient-provider interaction timepoints under Medicaid managed care settings was proposed in this dissertation. This model has practical applicability for managed care organizations and can help improve the patient selection process for intervention planning, particularly for services targeting the social determinants of children's health and wellbeing.

For improving maternal care quality, the causes of the persistently high interstate variations in cesarean rates were investigated and their implications on financial and adverse health

outcomes were analyzed. Finally, the impact of the Florida Statewide Medicaid Managed Care (SMMC) programs on pediatric and maternal care outcomes were estimated with a focus on reducing racial and ethnic disparities. After the SMMC implementation, there was a substantial reduction in several pediatric and maternal care outcomes and associated disparities. The findings of this study could help state policymakers understand the current performance of existing SMMC programs in reducing care disparities as well as facilitate the design of better policies and managed care contracts.

In summary, through the development of these six studies, this dissertation comprehensively provides novel insights and introduces innovative decision support approaches considering all major Medicaid stakeholders, which can be used to better design Medicaid pediatric and maternal care delivery systems.

Chapter 1: Introduction

1.1 Backgrounds

The overall healthcare spending in the United States is the highest in the world with an average of 18% of its gross domestic product (GDP) over the last 10 years.[1] Healthcare spending per person in the U.S. is almost two times higher compared to the most other wealthy countries, mainly driven by a higher tendency to utilize high-cost healthcare resources (e.g., emergency department visit vs primary care treatment).[2–4] However, this higher healthcare spending has not transformed into improved quality of care. The U.S. ranks lowest compared with the other industrialized countries on many measures including care access, health outcomes, quality, and efficiency.[2,5,6] Therefore, reducing healthcare expenditure and improving care quality has been a major policy concern in the U.S., and several critical legislations (e.g., Affordable Care Act) and programs (e.g., Hospital Readmissions Reduction Program) have been implemented in the last decades.[7,8] These efforts result in improvement in adult healthcare care quality, particularly for targeted elderly populations.[9] Compared to the elderly and private insured population, health outcomes and care quality in children and during maternal care remained unchanged, and one study even reported worsened pediatric and obstetric care conditions in recent years.[10–12] The U.S. now ranks 39th for overall child health and well-being while ranking worst in maternal care when compared with 10 other developed nations.[12,13] Particularly, in terms of preventable hospital visits and avoidable maternal morbidity/death, the U.S. is the highest proportion compared with the peer nations.[4,12] Besides, the rate of cesarean sections in the U.S. is among highest among advanced

nations, almost 2.5 times rate than in the lowest country.[10] Henceforth, the US healthcare system continues to face substantial challenges in improving care quality and reducing cost in pediatric and obstetric care. In the US, nearly half of all pre-post-natal care and more than one third of the children healthcare provision are covered through the federal and state joint funded Medicaid program.

Medicaid plays a critical role in ensuring health care needs for over 28 million children and 2.2 million births annually in the U.S..[14] Medicaid healthcare expenditures for children and maternal healthcare constitute a substantial proportion of the total federal and state budget. In 2018, total federal Medicaid spending was $96 billion and $34 billion for children and maternal healthcare and excepted to a substantial increase in the future.[15] According to Kaiser founder 2019 reports, the majority of the Medicaid spending went to the mandatory managed care programs covering more than 75% of total Medicaid beneficiaries in the US.[14] The average spending per enrollee in Medicaid covered children is almost similar compared to private insurance and marginally lower for during maternal care, compared with commercially insured mothers.[16] Although there is marginal spending difference with private payers and increasing expenditure for Medicaid population, the overall health and wellbeing of the Medicaid managed care beneficiaries have not improved significantly compared with the privately insured population.[15,17] Medicaid beneficiaries have higher rates of hospital usages (e.g., higher ED visits and readmission rates), higher mortality, and longer hospital stays than commercial insurance. Furthermore, Medicaid beneficiaries expected substantial racial and ethnic disparities in access to care (timely primary/specialist/OB-GYN care), preventive (e.g., pediatric well-care visits and care experiences), and care experience.[18–22] Therefore, the objective of this dissertation is to discover new knowledge regarding care fragmentation and disparities in pediatric and maternal care health

outcomes and develop data-informed decision support that aiming at reducing associated adverse health outcomes under Medicaid managed care settings.

In this dissertation, the overall research objective will be addressed by targeting three healthcare quality metrics in pediatric and maternal care. Three critical care quality metrics are (1) preventable Emergency Department (ED) visits, (2) preventable readmission, and (3) low-risk cesarean delivery. Preventable hospital visits in pediatric and maternal care are an important metric to assess patient care quality for clinicians, insurers, and healthcare providers. Preventable hospital visits are costly and often associated with adverse health outcomes.[23–25] The total hospital charges of pediatric pediatric preventable ED visits and readmissions within 30-days is around $21 billion, while postpartum preventable hospital visits resulted in a total in-hospital cost of around $2 billion.[26] Besides, low-risk cesarean rates have also become a critical metric in assessing maternal care quality for healthcare providers. Cesarean delivery is also costlier and associated carries short and long-term risks for both the mother and child than vaginal delivery.[27,28] Reducing unnecessary low-risk cesarean could potentially reduce overall healthcare expenditures and associated adverse health outcomes.

Improving these pediatric and maternal care quality outcomes is particularly important under managed care settings since the majority of the children and pregnancy health care provision were covered through various managed care programs. Medicaid managed care organizations (MCO) usually share most of the financial risk by state contract and, thereby highly incentivized to reduce unwarranted costs such as preventable hospital visits, and unnecessary cesareans while improving the quality of care.[29,30] MCOs have broad flexibility to cover services delivered via various care settings, therefore, using new knowledge and improved patient selection predictive analytics, managed care programs can implement targeted interventions to reduce the risk for

subsequent adverse health events. Therefore, the rationale underlying this investigation under MCO setting is that, providing novel knowledge regarding care fragmentation, preventable hospital visits, and low-risk cesarean and developing a holistic framework of decision support for all MCO stakeholders to reduce these preventable incidences, which provide opportunities to improve pediatric and maternal care outcomes and therefore reduce overall healthcare expenditures. An MCO care setting generally comprises four main stakeholders, (1) State policymakers, (2) Managed care programs, (3) care providers and, (4) patients. Each of these MCO stakeholders plays a critical role in assuring adequate healthcare provision among the beneficiaries. State policymakers establish the framework of overall care context through appropriate coverage and health service regulations. Managed care programs operationalize financial elements, enroll beneficiaries and provide care service to enrolled beneficiaries through dedicated care providers. The research studies presented in this dissertation provide novel insights and introduce decision supports approaches considering independently all four major MCO stakeholders, which they can use to better design a more effective and comprehensive healthcare delivery system.

1.2 Research Contributions

The research contributions of this dissertation are described as follows.

1. In the first study (chapter 2), I quantified the state and national trends in pediatric care fragmentation in the context of index vs non-index readmission, identified significant risk factors, and determine whether this destination difference affects readmission outcomes. In addition, I explored the recent geographical variation of pediatric non-index readmission across Florida State. This study highlights the persistence of pediatric care fragmentation after the initial hospitalization and provides insights regarding the contributing factors and adverse health implications of these non-index pediatric readmissions.

2. In the following study (chapter 3), I proposed a novel pediatric readmission prediction model at the time of hospital admission that can improve the high-risk patient selection process, with the possibility of early pediatric readmission risk prediction. Proposed early readmission risk decision support model can help to admitting hospitals and providers additional time for intervention planning, particularly for those targeting social determinants of children's overall health.
3. In the next study (chapter 4), I proposed cohort-specific pediatric readmission predictive models that can achieve higher discrimination compared with the traditional all-cause readmission models. Since pediatric readmissions vary greatly (~3%-30%) depending on the index diagnosis and I hypothesized that a single all-cause model for readmissions prediction in a clinical setting may be insufficient. Subsequently, I constructed cohort-specific predictive models based on supervised machine learning algorithms to identify children with the risk of 30-day readmission for two acute and three chronic conditions and compared them with the performance of the all-cause readmission model. Machine-learning models I developed in this study improved the readmission prediction for the majority of pediatric conditions compared with the all-cause readmission model. In addition, I identified several novel significant readmission risk factors in this study and compared them across different index conditions to better understand the opportunities to design future targeted interventions.
4. In the study introduced in chapter 5, I proposed a novel framework of preventable ED visits and revisit prediction models at the timepoints when MCOs generally receive information regarding patient's information from providers or self-reported by the children's parents. This framework and prediction models have pragmatic applicability for the MCOs

covering children's healthcare and can help physicians and providers with the improved patient selection process for intervention planning, particularly for those targeting social determinants of children's wellbeing and health. Therefore, this study comprehensively highlights managed care program's potential to reduce avoidable pediatric ED visits through comprehensive machine learning-based predictive models and provides important insights regarding the influencing factors of preventable ED visits and economic impact in the Florida State Medicaid program.

5. In the following study (Chapter 6) focusing on maternal care quality outcome, I explored the causes of the persistent high variation in interstate cesarean rates and their financial and clinical impact on health outcomes. The rationale for this study is that an improved understanding of the realities of existing differences in intrastate cesarean rates and associated outcomes is crucial to state policymakers for developing new action plans or restructuring state Medicaid programs with a goal of more comprehensively meeting public health needs. Using a novel non-linear extension of the Oaxaca-Blinder method I decompose the contributions of differences in characteristics to cesarean variations for Florida, New York, and Wisconsin State. The cesarean variations explained by this study are considerably greater than those of a prior study (~30.7–43.7%) in the United States. In a novel analysis, I found that social determinants of health and admitting hospital characteristics (e.g., higher markup ratio) determinants explained the largest proportion of the differences in state cesarean rates. Since non-clinical factors are likely to play an important role in an increased cesarean rate and variations, insight from this study could help managed care providers and policymaker to devise interventions, including improving access to maternal care, training for patients with low-risk pregnancies for state-specific

high-risk groups (e.g., Hispanic/Latino), and restructuring the reimbursement schemes of for-profit hospitals (e.g., bundled payment).

6. After finding new insights about pediatric and maternal care outcomes and the development of novel decision support that can improve prediction of these outcomes, I investigated the impact of State of Florida mandatory managed care (SMMC) programs in reducing pediatric preventable hospital visits, care fragmentation, and maternal care outcomes, particularly focusing on persistent racial/ethnic disparities (see Chapter 7). This is the first study to analyze Florida SMMC's impact on pediatric and maternal care quality and explore the association between SMMC implementation and racial/ethnic disparities. In this study, the estimation showed evidence of a substantial reduction in several pediatric care outcomes (e.g., preventable hospital visits and revisits) and maternal care outcomes (postpartum revisits and readmission rates) for the Medicaid population compared with the privately insured patient population. Besides, I also estimated the financial impact of SMMC due to potentially preventable hospital encounters for Medicaid pediatric and obstetric care patient populations. Therefore, the study highlights the overall impact of SMMC on pediatric and obstetric healthcare quality in Florida State; and provides important insights regarding the positive dynamics and potential scope for improvement in care quality and associated racial/ethnic disparities among the Medicaid population.

In summary, the work presented in this dissertation provides important novel knowledge about Medicaid pediatric and maternal care quality to better understand the improvement scope in care quality and to reduce associated racial/ethnic disparities for all stakeholders in Managed care settings. The novel decision support system we proposed in this dissertation would help hospital administrators and managed care programs to better design comprehensive clinical and non-

clinical interventions that can reduce preventable adverse health outcomes and consequently reduce healthcare expenditures. Furthermore, findings of our study could also help Florida State Policymakers to better understand the existing performance of the SMMC program in reducing disparities in care delivery and, could facilitate the design of better policies and Managed care contract with optimal levels of incentives that will directly stipulate MCO programs to enhance the care provisions to the vulnerable population in need and indirectly improve hospital care quality, and reduce overall healthcare expenditures.

Chapter 2: Characteristics and Health Outcomes of Pediatric Readmission to Index Versus Non-index Hospitals

Increasing pediatric care regionalization may inadvertently fragment care if children are readmitted to a different (non-index) hospital rather than the discharge (index) hospital. Therefore, this study aimed to assess trends in pediatric non-index readmission rates, examine the risk factors, and determine whether this destination difference affects readmission outcomes. This retrospective cohort study uses the Healthcare Cost and Utilization Project State Inpatient Database to include pediatric (0-18 years) admissions from 2010 to 2017 across Florida hospitals. Risk factors of non-index readmissions were identified using logistic regression analyses. The differences in outcomes between index vs. non-index readmissions were compared for in-hospital mortality, morbidity, hospital cost, length of stay, AMA discharges, and subsequent hospital visits using generalized linear regression models. Among total 41,107 identified readmissions, 5,585 (13.6%) were readmitted to non-index hospitals. Adjusted non-index readmission rate increased from 13.3% in 2010 to 15.4% in 2017. Patients in the non-index readmissions group were more likely to be adolescents, living in poor neighborhoods, have higher comorbidity scores, traveling longer distances, and be discharged at the post-acute facility. After risk adjusting, no difference in in-hospital mortality was found, but morbidity was 13% higher, and following unplanned ED visits were 28% higher among patients with non-index readmissions. Length of stay, hospital costs, and against medical advice discharges was also significantly higher for non-index readmissions. This study highlights the persistence of pediatric care fragmentation after the initial hospitalization and

provides insights regarding the contributing factors and adverse health implications of these non-index pediatric readmissions. The complete manuscript titled Characteristics and Outcomes of Pediatric Non-index Readmission: Evidence from Florida Hospitals, currently accepted (In Press) in Hospital Pediatrics can be found in Appendix C.

Chapter 3: Identifying Children at Readmission Risk: At-Admission Versus At-Discharge Readmission Prediction Model

Unplanned pediatric hospital readmissions are costly and often associated with adverse health outcomes and therefore have become a major policy concern. Therefore, readmission reduction efforts in the pediatric patient population gained significant attention to researchers more recently in devising ways of reducing readmission risk among children. An improved readmission reduction model can help hospitals and healthcare providers to identify high-risk patient groups and therefore, implement interventions on time that reduce the risk of unplanned admission within 30 days of hospital discharges. Previous pediatric readmission studies are thus far limited to the development of a prediction model after patient hospital discharges. Since the timing of the pediatric readmission is highly skewed (~40% of the occurred within 7 days) and there is a delay between information exchange between healthcare providers, which might provide limited time to the hospital to devise a comprehensive intervention plan. Therefore, in this study we propose, a novel pediatric readmission prediction model at the time of hospital admission to improve the high-risk patient selection process and compared the proposed model with the existing at-discharge model.

Using the Hospital Cost and Utilization Project database, this prognostic study included pediatric hospital discharges in Florida from January 2016 through September 2017. In this study, we evaluated the pediatric readmission prediction model using patient information and available data for two major time points, (1) prediction model that uses data available at the time of hospital

admission or transferring to another acute care hospitals (AD-PDR), (2) tradition readmission prediction model (DS-PDR) that uses all available information during discharge time. Four machine learning algorithms including logistic regression (LR) with backward stepwise selection, Decision tree (C4.5), Support Vector machines (SVM) with the polynomial kernel, Gradient Boosting (GB) algorithms were developed for at-admission and at-discharge model using a recursive feature elimination technique with a repeated cross-validation process. The performance of the AD-PDR and DS-PDR models was measured by the area under the curve (AUC). The performance of the at-admission model was comparable with the at-discharge model for all four algorithms. SVM with Polynomial Kernel algorithms outperformed all other algorithms for at-admission and at-discharge models. Important features associated with increased readmission risk varied widely across the type of prediction model and were mostly related to patients' demographics, social determents, clinical factors, and hospital characteristics. To our knowledge, this is the first study to develop an at-admission pediatric readmission model and compared prediction performance with the traditional at-discharge readmission prediction model. In addition, our proposed revised AD-PDR models excluding two-body system diagnosis showed improved and almost similar prediction performance compared with the DS-PDR model. Proposed early readmission risk decision support model can help to admitting hospitals and providers additional time for intervention planning, particularly for those targeting social determinants of children's overall health. The complete manuscript titled "Identifying Children at readmission Risk: At-admission versus at-discharge readmission prediction model", under review (under second revision) in the International Journal of Intelligent System, can be found in Appendix D.

Chapter 4: Identifying Children at Readmission Risk: Cohort-Specific Versus All-Cause Readmission Prediction Model

Although pediatric readmissions are costly and potentially preventable, accurately predicting and reducing readmission risk in children remains challenging. Machine learning has the potential to improve predictive power by identifying complex-nonlinear relationships within datasets. Our objective was to assess whether machine learning can better identify readmission risk in children hospitalized for common pediatric conditions. Using the Hospital Cost and Utilization Project database, this prognostic study included pediatric hospital discharges access non-federal hospitals in Florida from January 2016 through September 2017. Five machine-learning algorithms (random forest, naïve Bayes, support vector machines, adapting boosting, neural networks) were compared with the traditional approach (logistic regression and all-cause readmission) to predict 30-day unplanned readmission for two acute (appendicitis and pneumonia) and three chronic (asthma, seizure, and sickle cell) conditions. The model's performance was measured by the area under the curve (AUC). Risk factors were identified using multivariate regression techniques. The performance of the best model varied widely depending on the index diagnosis, with average AUC ranges from 0.60 for appendicitis to 0.71 for pneumonia. Compared with the logistic regression, machine-learning algorithms showed considerable improvement in AUC for asthma, seizure, and pneumonia. Depending on the admission causes, factors such as higher comorbidity score, readmissions history, post-acute discharge, race, and certain social determinants of health factors were associated with increased risk of readmissions. Condition-

specific machine-learning methods improved the readmission prediction in most pediatric conditions. Significant risk factors varied widely by index diagnosis, indicating disease-specific multifaceted intervention plans may help to reduce adverse pediatric outcomes. The complete manuscript titled “Identifying Children at Readmission Risk: Cohort-specific versus all-cause readmission prediction model”, under review in the Machine Learning with Applications Journal, can be found in Appendix E.

Chapter 5: Predicting Preventable Pediatric Hospital Visits and Revisits Under Medicaid Managed Care Settings

5.1 Backgrounds

Emergency Departments (EDs) in the United States play a critical role in ensuring health care needs for 365 million Americans. Any patient in the U.S. can receive treatment in EDs regardless of their ability to pay due to legal mandate and treatment is available 24 hours throughout the year, which defines ED primary safety net for many patients, especially for vulnerable populations.[31] According to the Centers for Disease Control and Prevention (CDC), more than 145 million times patient received emergency care in 2016 at the U.S. hospital EDs with an overwhelming 20.8% increment form from 120 million in 2006.[32] Among those visits, more than 30 million visits (20% of total visits) were for children and of which, only 3.4% resulted in pediatric inpatient hospitalization while adult hospitalization rate is substantially higher of 19.74%. The majority (in some states more than two-third, e.g., 68% in Florida State) of these pediatric ED visits were covered by state-specific Medicaid programs and children's health insurance coverage.[33–35] Many children from minority races and ethnicity, public insurance, uninsured and low-income status family depend on the ED for healthcare needs instead of a usual source of care.[36]

Although ED visits are necessary for treating critical patients such as injury and acute conditions, a substantial proportion (~14%-66%) of the visits, particularly visits with low acuity conditions may not need emergency care and can be treatable to other care settings.[37] In addition to lack of insurance coverage and after-hours care, there might be other reasons for this high ED

utilization such as superior quality of treatments, delays in scheduling in primary care physicians /specialist, patient belief about the seriousness of their conditions, and lack of available information about other sources of treatment.[38,39] Children with Medicaid coverage, historically monitory race, and living in disadvantaged communities have significantly lower access to care compared with commercial coverages and children living in metro areas.[40–42] Besides, the high degree of pediatric care regionalization may also intensify the care access barrier, particularly in rural areas.[43,44] Consequently, the disproportionality in care access may result in the unprecedented increase in ED utilization for patients with Medicaid insurance coverage, particularly children and families living in disadvantaged communities.[35,45]

The increase in ED utilization hurting the overall U.S. healthcare systems with critical problems such as ED overcrowding, longer boarding time, delay in receiving initial treatment, lower patient satisfaction.[34,46,47] Besides, the treatment cost in ED is substantially higher (average treatment cost \$600) than in urgent care (average cost \$200) or care provided physician office (average cost \$100).[48] The aggregate cost of outpatient ED visits comprises a substantial portion (12.5%) of the US healthcare budgets with a total of \$328.1 billion.[49] Several studies reported that almost nearly half of the total outpatient ED expenditures could be saved if patients with preventable ED visits were treated in the alternative care setting.[50,51] This large proportion of preventable ED visits suggest systematic inadequate care management, disparities in access to care, and uninformed choices from the patient's ends.[52] In addition, lack of post-discharge follow-up and other complex social, and behavioral reasons, patients discharged from ED may potentially return for non-emergent care, eventually become ED super-utilizers.[45,53] ED super-utilizers are only a few (4% of total unique patients), comprise more than 20% of the total ED visits and the majority of these visits are potentially preventable.[39,47,51] Children, particularly with Medicaid

generally belong to the high ED utilization group and are often characterized with the high frequency (17% return rete reported in one study) of ED return visits after Treat and release ED treatment.[52,54] Therefore, reducing preventable ED visits has become a major policy concern for healthcare providers, public health officials, and state policymakers.[34,55,56] Consequently, many state Medicaid programs implemented or plan to implement quality metrics that track preventable ED utilization and provide incentives or reduce payments to Managed Care Organizations (MCO) with over threshold preventable ED visits utilization.[57,58]

5.1.1 Problem Definition

As the researchers gained extensive understanding of the sophisticated dynamics of ED visits, different health care providers explored various interventions or programs to reduce interventions to reduce ED use.[59] Interventions implemented at EDs (e.g., follow up and case management) and outside of ED (patient education, need-based assistance programs and improved care access) were reported in prior studies to the risk of ED utilization with a various level of effectiveness.[60,61] Any successful ED utilization reduction programs generally require a comprehensive array of both ED and outside ED interventions and the effectiveness of the program depends on the right high-risk patient selection.[60,61] With the wide adoption of electronic medical records and health information exchange systems, ways to reduce preventable hospital ED visits have focused on predictive analytics to identify high-risk patients.[62,63] Preventable ED visits prediction models potentially enable direct general or patient-specific interventions toward those who might need most by identifying high-risk patients. Predicting preventable ED visits and super-utilizers for the adult patient population has been the subject of substantial research and tackled by diverse predictive approaches.[62–65] However, preventable ED visits and revisit predictions for children have received limited attention.[61,63,66] Most studies in pediatric readmission are thus far

limited to the examination of patient populations susceptible to high ED utilization and ED return visits.[33,66,67] Only one study thus far implemented a machine learning-based prediction model and showed promise in predicting returning pediatric visits across Italian EDs.[52] However, this study has limited practical applicability in predicting US pediatric EDs visits, mainly due to the difference in the healthcare system.

In the U.S., many particular healthcare systems such as Medicaid Managed Care organizations, are responsible for proving healthcare for a group of distinct populations and can make decisions using information such as patient-centered interventions that ensure better access to care.[68] Studies showed that effective ED utilization reduction programs should be aligned with the healthcare organizational structure along with a comprehensive set of interventions.[59] However, no studies thus far have developed a holistic and practical data-informed decision support for predicting high-risk preventable pediatric ED visits under distant healthcare delivery systems such as Medicaid Managed Care Organization (MCOs). Developing a comprehensive framework under the MCOs that can identify preventable pediatric ED visits is critical for multi-factorial reasons. First, the total number of Medicaid pediatric hospital visits has been increased 51% from the year 2006 to the year 2015 while ED visits for commercial payer has been decreased by 28.2%.[69] Second, nearly half of the children's ED visits are covered by Medicaid insurance and more than 70% of those visits were covered by MCOs.[69] Medicaid population generally comprised of historically minority race and ethnic children living in disadvantaged conditions and associated with substantially higher ED utilization. Therefore, an improved high-risk patient selection process under MCOs setting could substantially reduce overall pediatric ED utilization and consequently reduce healthcare expenditures. Third, due to the state-MCO contract and benefits structure, MCOs are responsible for providing healthcare for a certain patient population through the capacitated

payment system. Therefore, by identifying high-risk ED utilizers under MCOs setting, MCOs can immediately implement interventions such as a need-based assistance program or increasing access to primary care to reduce the need for subsequent ED visits. Therefore, it is crucial to develop a holistic preventable pediatric ED visits risk prediction framework and machine learning-based models under MCOs settings, that can identify high-risk patients and can be coupled more effectively with appropriate intervention programs, and ultimately improve quality of care.

5.1.2 Research Objectives

Our study hence aimed to develop prediction models that can better identify those children that are at high risk of unplanned hospital ED visits and revisits after 30-days of hospital visits. In this study, we propose a novel framework of ED visits prediction models at the timepoints when MCOs generally receive information regarding patient’s information from providers or self-reported by the children’s parents. We hypothesized this framework and prediction models would have pragmatic applicability for the MCOs covering children's healthcare and helped physicians and providers improved patient selection for intervention planning, particularly for those targeting social determinants of children's overall health.

5.2 Materials and Methods

5.2.1 Proposed Modeling Framework

We proposed a holistic framework of the high-risk patient selection process under Medicaid managed care settings (Figure 1). Medicaid managed care organizations generally receive capacitated payments from state Medicaid for a certain patient population and responsible for providing health benefits and additional services to their beneficiaries. Since, MCOs are sharing the majority of the financial risk by state contract design, managed care programs are highly incentivized to reduce unwarranted costs (such as preventable ED visits and revisits) while

improving the quality of care. Many states also implementing other MCO initiatives that focus on improving care quality for the disadvantaged population through aligning payment incentives with performance targets. Therefore, we based our proposed framework on preventable ED visits and revisits prediction on the current MCO working hierarchy and exchange of information between MCO and other healthcare providers, so that MCOs can identify high-risk patients and implement appropriate intervention strategies to reduce the risk of ED utilization.

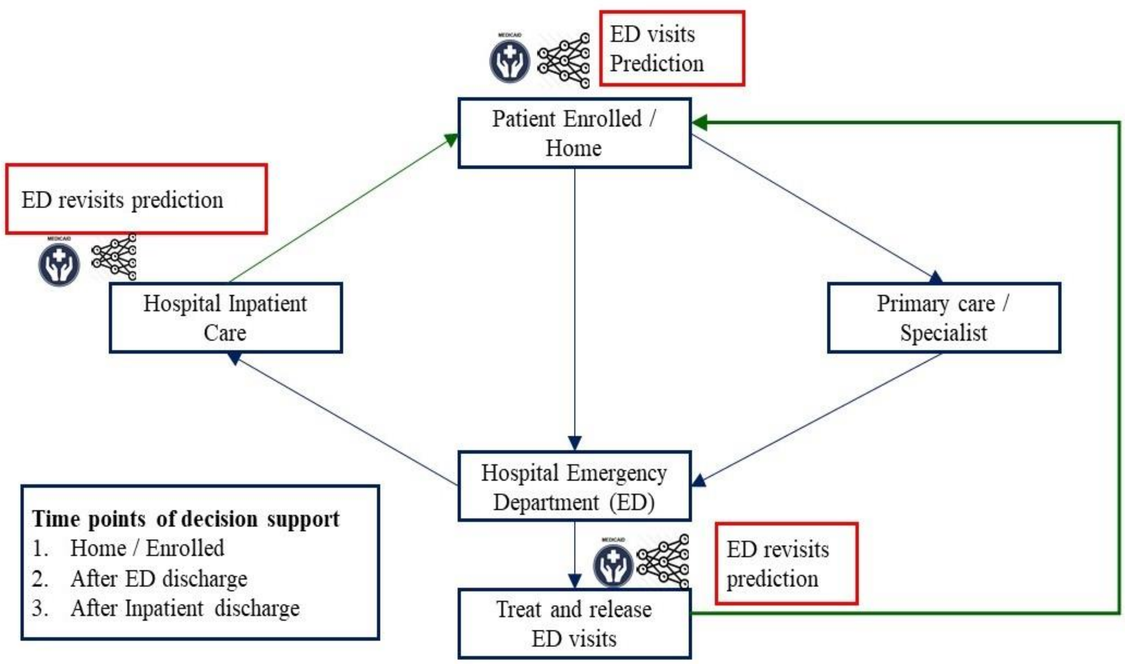

Figure 5.1: Preventable ED visits and revisits prediction model under managed care settings

Under the current Health information exchange framework, MCOs generally receive patient information at three major points of beneficiary contact. MCO receives administrative claim information (ICD codes) from hospitals right after enrolled beneficiaries received treatments from hospital EDs (Treat and release ED) visits and treated in the hospital inpatient care setting (Inpatient care visit). These two patient-provider encounters are particularly important since MCOs can only receive detailed patient diagnoses and procedures during that timepoint. Besides,

MCOs strongly motivate hospitals and other providers to include ICD SDH codes, so that high-risk patient groups can be identified since SDH variables significantly affect people's wellbeing and hospital resource utilization. The MCOs can also receive information from another important but often ignored timepoint of beneficiary enrollment. During the enrollment, beneficiary self-reported information including social determinants and prior hospital visits history can also be used to predict high-risk ED users. Therefore, we proposed the pediatric ED visits and revisit prediction model using patient information and available data for three major time points, (1) preventable ED visit prediction model that used information available during beneficiary enrollment (EN-PDR), (2) preventable ED revisit prediction model that uses data available at the time of hospital treatment and Release ED visits or transferring to another acute care hospitals (ED-PDR), (3) preventable ED revisit prediction model that uses data available at the time of inpatient hospital discharges (IP-PDR).

5.2.2 Study Design, Data Source, and Participants

We conducted a retrospective observational study of pediatric hospital visits from January 1, 2016, to September 30, 2017, across all Florida’s hospitals, using the Hospital Cost and Utilization Project (HCUP) all-payer State ED (SED) visit and State Inpatient Databases (SID). The SED and SID database is an administrative all-payer database including the uninsured, which is maintained and certified by the Agency for Health Care Research and Quality (AHRQ). The HCUP Florida SID and SED data contain patient-level information on demographic characteristics, insurance status, and International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10-CM) diagnosis and procedure codes, patient location, and hospital charges of all ED and ED-admitted inpatient visits from 265 acute care hospitals in the 67 counties in Florida. Data on admitting hospital information were obtained from the American Hospital

Association (AHA) annual survey. Data on hospitals, including geo-locations, were obtained from the American Hospital Association hospital guide. Data on community-level health determinants were derived from the American Community Survey (ACS) by linking patient ZIP codes through Uniform Data System (UDS) Mapper crosswalk.[70] We excluded all adult patients (>18), residential addresses outside Florida, discharges against medical advice (AMA), and cases of in-hospital mortality from the dataset. HCUP databases are considered limited datasets as determined by the local Institutional Review Board and therefore institutional review board review approval is not required for this project.

5.2.3 Outcome Measures

The primary outcome was preventable ED visits and preventable ED revisits within 30 days following Treat-and-release ED and inpatient care discharge. Preventable ED visits were classified using the NYU-ED Billing Algorithm developed by the New York University Center for Health and Public Service Research.[71] This previously validated algorithm assigns probabilities to each ED visit as (1) emergent-not preventable/avoidable, (2) emergent but preventable or avoidable, (3) emergent but primary care treatable, and (4) non-emergent.[72,73] We assigned each ED visit to the potentially preventable category if the combined assigned probability for categories (3) non-emergent and (4) emergent but primary care treatable is greater than 50%.[74,75] An 30-days ED revisits are defined as the treatment and release of ED utilization for any unplanned or preventable causes occurring within 30 days of index ED or inpatient care discharge. Unplanned or preventable causes for ED revisits were identified with the similar approach above using NYU-ED Billing Algorithm. Only the first ED revisits within 30 days were considered and subsequent encounters after 30 days from discharge were identified as another index ED counterturns.

5.2.4 Predictor Variables

Predictors for the three preventable ED utilization prediction model models, at managed care beneficiary enrollment point (EN-PDR), after Treat-and-release ED encounter (ED-PDR), and at-inpatient care discharge prediction model (IP-PDR) were included based on the availability of the information at that certain time point of care (Table 5.1). EN-PDR models included patient demographics, socioeconomic status, provider density, prior hospital visit history, and community-level social determinants of health. ED-PDR models all variables included in the EN-PDR model, diagnosis and procedures presented at the time Treat-and-Release ED visits, discharge disposition, and vising hospitals information. Finally, ED revisits prediction models (IP-PDR) after inpatient discharge included all variables included in the ED-PDR model, inpatient diagnosis, procedures, discharge disposition, inpatient care duration, and admitting hospital's detailed information.

Table 5.1: Predictor variables for the three pediatric readmission prediction models

Variable Type	Prediction model before admission (PT-PDR)	Prediction model at admission (AD-PDR)	Prediction model at Hospital discharge (DS-PDR)
Demographics	X	X	X
Socioeconomic status	X	X	X
Provider density	X	X	X
History of hospital visits	X	X	X
Community-level social determinants of health	X	X	X
Individual-level social determinants of health		X	X
Diagnosis at admission		X	X
Hospital characteristics		X	X
Hospital travel distance		X	X
Diagnosis during hospitalization			X
Hospital procedures			X
Discharge planning			X
Hospital length of stay			X

Demographic characteristics for each hospital visit included age (0-1, 1–5, 5–10, 11–14, 14–17 years), gender, race, and ethnicity (non-Hispanic white, non-Hispanic Black, Hispanic, and others). Community-level social determinants of health were used as proxy measures of patient socioeconomic conditions. The history of the patient's hospital visits was also included in our analysis. Provider density was considered as binary variables (high/low), low provider density is considered for if patients live in the designated medically underserved area (MUA) and counties. Designated MUA status was determined using the U.S. Health Resources and Services Administration (HRSA) classification.[76] Social determinants of health (SDH) variables considered in our study were the percentage of people with an income below 100% federal poverty level (FPL), the percentage of homes with no vehicles, the percentage of people with no high school diploma, and the Percentage of the unemployed person. These community-level SDH variables affected hospital visit behaviors reported in prior studies and included in our study at the ZIP code tabulation area (ZCTA) level, a generalized area representation of the ZIP codes used by the U.S. Census.[77] These predictor variables were used in developing the preventable ED visits risk prediction during the MCO enrollment (EN-PDR) model.

Hospital-level covariates are children's hospital status, location (metropolitan, and micro/rural), ownership status (for-profit and non-profit/government), and hospital bed size (large, medium, and small). Travel distances between patients' residences and discharge hospitals were calculated by geocoding using geographical information software (ArcGIS 10; Ersi Inc., Redlands, CA, USA). The hospital locations were geocoded based on the street addresses and patients' homes into geographic coordinates of home zip code geometric centroids.[44,78] Individual-level SDH variable was a binary variable indicating potential health hazards related to children's family conditions (e.g., housing and parent instability). The other patient characteristics were the day of

the week (weekend versus weekday), and ED discharge planning (routine, post-acute facility, and home health care), and referral by the physician. Post-acute facilities in our study were defined if the patient was discharged/ transferred to a skilled nursing, intermediate care, and another type of facility (e.g., Rehabilitation). Race and ethnicity were included in our study since that has been significantly associated with the differences in hospital care-seeking behavior.[79]

Table 5.2: Modeling parameters for machine learning algorithms

Method	Modeling parameter	Note
Logistic regression	None	
Naïve Bayes	Laplace Usekernel Adjust	Amount of Laplace smoothing = {0,0. 25..., 5.00} Type of density estimation = {Gaussian, kernel} Bandwidth of the kernel density = {0, 1…,5}
Support Vector Machines with Polynomial Kernel	Degree Scale Cost	Polynomial Degree = {0, 1….,5} Logical vector indicating variable to be scaled= {T, F} Controls model overfitting = {0.25,0. 50….,5.00}
Multilayer Perceptron Neural Network	Layer 1 Layer 2 Layer 3 Decay	Number of hidden units layer1= {1,2….,10} Number of hidden units layer2= {0,1,2….,10} Number of hidden units layer3= {0,1,2….,10} Regularization parameter weight decay= {0,10^{-1}…, 10^{-4}}
Adapting Boosting	nIter method	Number of classifiers tree= {0, 1….,50} Type of Adapting Boosting = {Real AdaBoost, AdaBoost.M1)
Random Forest	Mtry Tree	Number of randomly selected predictors = {1, 2…,12,17} Number of trees, fixed to 1000

The ICD-10-CM primary diagnosis and procedures codes are used to characterize hospital visits by patient disease complexity. Patient complexity for each visit was divided using previously developed 3-tiered categorical variables of no chronic condition, noncomplex chronic condition, and complex chronic condition (CCC).[80–82] Patients with CCC were identified using a previously validated approach as any medical condition expected to last at least 12 months with multiorgan or severe single-organ involvement necessitating pediatric subspecialty care.[81] For those without a CCC, we then categorized patients with no chronic condition and noncomplex chronic condition using the Agency for Healthcare Research and Quality’s (AHRQ) Chronic Condition Indicator.[80] ED-PDR prediction models included all variables discussed above and variables included in the EN-PDR model. For the ED revisit prediction models (IP-PDR) after inpatient discharge,

comorbidity conditions measures were extracted from 30 ICD-10CM inpatient diagnoses and procedures. The IP-PDR model included all variables included in the ED-PDR model and length of inpatient stay (0–3, 3–8, and ≥ 8 days).

5.2.5 Modeling and Analysis

All hospital visits were categized into three groups, for developing at enrollment preventable ED visit prediction model, preventable ED revisits after outpatient ED encounters and preventable ED revisit after inpatient care. The patient cohort for EN-PDR models was selected for single ED visits before 18 years and first visits for multiple ED and Inpatient care visits. ED-PDR and IP-PDR patient cohorts were identified for ED and inpatient care visits that resulted in ED visits within 30 days of the discharge. The overall missing data rate was <0.5%, which we imputed using multiple stochastic chained equations.[83] Multicollinearity between candidate variables was also assessed using the variance inflation factor analysis.[84] We used a repeated five-fold cross-validation process to evaluate the performance of the prediction model (Figure 2). First, each disease cohort's entire dataset was divided into 5 equal cross-validation folds for the repeated cross-validation process. For each cross-validation repetition, each fold is alternatively used as the test dataset while training our predictors on the other remaining folds. Hyperparameter tuning for each fold was also conducted during model training to further optimize the model performance. The Hyperparameter of each technique was optimized through a grid search with 10 repeated 5-fold cross-validation iterations. While training, we also explored the issues with class imbalanced problems by using the Synthetic Minority Over-sampling Technique (SMOTE) on the training dataset.[85]. We repeated the cross-validation process 50 times on each cohort dataset to obtain the average performance of each learning model.

Predictive models were developed using both classical and ensemble machine-learning algorithms for each model. For traditional methods, we applied logistic regression (LR) with backward stepwise selection, Naïve Bayes (NB), Support Vector machines (SVM) with the polynomial kernel, feed-forward Multilayer Perceptron neural network (MPNN) algorithms. For the ensemble methods, we used Adapting Boosting (AdaBoost) and Random Forest (RF) algorithms for preventable ED visits and revisits prediction modeling. Details of model development and hyperparameters are available in Table 5.2. The area under the receiver operating characteristics (ROC) curve (AUC) was used to evaluate the performance of each prediction model. We also identified significant risk factors using multivariate logistic regression for all three models. Effect sized was interpreted as odd ratios with a 95% confidence interval. All statistical analyses were performed using R studio, and a two-sided p-value less than 0.05 was considered statistically significant.

5.3 Results

The analysis included 1,683,385 hospital visits by 856,704 children from January 1, 2016, to September 30, 2017, of which 1595151 were Treat-and-release ED encounters and 88234 were hospital inpatient care. Among these hospital ED visits, an overwhelming 608,851 of them (51.7 % of total) were found potentially preventable. Including only Florida residents and Medicaid managed care coverage, the total number of Treat-and-release visits and inpatient hospitalization were 1,124,086 and 50389, respectively, which represent overall 66.7 % of total pediatric hospital visits. Out of these Medicaid-covered ED visits, the total number of first-time ED visits was 556, 329 which are included in our EN-PDR patient cohorts. The total number of preventable ED visit rates in this EN-PDR cohort was 310266 (55.7%) and slightly higher (P< 0.01) than over preventable ED visits rates. The ED-PDR patient cohorts included 1,045,073 index Treat-and-

release ED visits. Among them, 89,905 (8.65%) were found potentially preventable ED return visits that occurred within 30 days of initial ED discharges. Consequently, out of 50,389 inpatient discharges covered by Medicaid, a substantial proportion (4.2%) of children returned to the ED with conditions that could be preventable through other care settings. Therefore, the EN-PDR, ED-PDR, and IP-PDR cohorts included in total 1124086, 556 329, and 50389 hospital visits.

Table 5.3: AUC performance comparison of the predictive models

Machine learning Algorithms	Prediction during MCO enrollment (EN-PDR) (AUC, 95% CI)	Prediction after ED discharge (ED-PDR) (AUC, 95% CI)	Prediction after inpatient discharge (IP-PDR) (AUC, 95% CI)
Support Vector Machines with Polynomial Kernel	0.58 (0.56-0.62)	0.71 (0.68-0.73)	0.70 (0.68-0.72)
Logistic regression	0.59 (0.55-0.64)	0.69 (0.67-0.71)	0.72 (0.70-0.74)
Adapting Boosting	0.55 (0.52-0.58)	0.65 (0.61-0.69)	0.65 (0.63-0.67)
Random Forest	0.57 (0.55-0.59)	0.68 (0.66-0.71)	0.69 (0.66-0.72)
Naïve Bayes	0.54 (0.52-0.56)	0.65 (0.61-0.69)	0.66 (0.62-0.69)
Multilayer Perceptron Neural Network	0.57 (0.54-0.60)	0.66 (0.63-0.69)	0.67 (0.64-0.70)

5.3.1 Economic Impact

The total hospital charges for pediatric Treat-and-Release ED visits were $4.1 billion with an average of $2665 per pediatric ED visit. Among the total hospital charges, a substantial proportion of $2.7 billion charges (average cost $2541) were for Medicaid managed care ED visits. The average hospital charge for potentially preventable pediatric ED visits was $2325, and total preventable ED visits related to hospital charges were $1.9 billion for the combined study period ($ 1.1 billion in 2016). The total preventable ED visit charges covered by various MCO programs in Florida state was $1.35 billion (average $2234) from January 1, 2016, to September 30, 2017.

Particularly, in 2016 the total annual total hospital charges for Medicaid preventable ED visits were $800 million for Florida residents.

5.3.2 Prediction Performance Comparison

Table 5.3 summarizes the comparative performance of six machine learning algorithms for three different prediction models. LR and SVM with Polynomial Kernel ranked top two compared to the other algorithms for all three prediction models. Conversely, the AdaBoost and MPNN models did not rank the top three for any prediction model. LR models outperformed all other algorithms for EN-PDR and IN-PDR models, while the SVM with polynomial kernel model outperforms other algorithms for ED-PDR models. The performance of the preventable ED revisits prediction model after inpatient care discharge (IP-PDR) was slightly higher with the after Treat-and-release ED discharge (DS-PDR) model for all algorithms, except for the SVM algorithm. For the EN-PDR models, the average AUC and 95% confidence interval (CI) for the SVM, LR, AB, NB and MPNN models were 0.58 (0.56-0.62), 0.59 (0.55-0.64), 0.55 (0.52-0.58), 0.57 (0.55-0.59), 0.54 (0.52-0.56) and 0.57 (0.54-0.60) , respectively. The average AUC and 95% CI for ED-PDR models for for the SVM, LR, AB, NB and MPNN models were 0.71 (0.68-0.73), 0.69 (0.67-0.71), 0.65 (0.61-0.69), 0.68(0.66-0.71), 0.65 (0.61-0.69) and 0.66 (0.63-0.69), respectively. Finally, the average performance above mention six algorithms for IP-PDR models were 0.70 (0.68-0.72), 0.72 (0.70-0.74), 0.65 (0.63-0.67), 0.69 (0.66-0.72), 0.66 (0.62-0.69) and 0.67 (0.64-0.70), respectively.

5.3.4 Factors Associated with Preventable ED Visits and Revisits

Results from multivariate regression analyses for all three model cohorts are shown in Table 5.4. Significant Factors associated with the increased preventable visit and revisit risk were almost similar with few exceptions across different cohorts and were mostly related to patients' demographics, SDHs, clinical factors, and hospital characteristics. The history of prior hospital

ED visits was found significant across all patient cohorts. More than three prior hospital visits were associated with a higher likelihood of revisits in the IP-PDR cohort than in EN-PDR and ED-PDR models. Children living in low healthcare provider density were found with higher preventable ED visits risk for all three prediction models than high-density areas. Gender was found significant in ED-PDR and EN-PDR cohorts, with a higher likelihood of ED visits for female patients. Age also found significant factors in all cohorts and children aged 8 to 12, and adolescent children were significantly associated with increased ED visits and revisits risk. Furthermore, Non-Hispanic African American and Hispanic children have higher odds of preventable ED visits than non-Hispanic white children.

Children living closer to index hospitals and those who were admitted to children's hospitals were less likely to be returned to ED care compared with adult hospitals and living far from the hospitals. Discharges to post-acute facilities have higher odds of being returned to the ED care than routine discharge in both patients discharged from ED and inpatient care. The presence of complex and non-complex chronic conditions were also significant predictions of preventable ED return visits. For the IP-PDR patient cohort, the length of stay was identified as significant and the longer patient has stayed in the hospitals, the higher the likelihood of returning to ED within 30 days of index discharge. Social determinants were also found significant in regression analysis and varied widely across the three models. Children living with challenging family conditions and in disadvantaged neighborhood neighborhoods were associated with an increased risk of preventable ED care for both ED-PDR and IN-PDR models. Living within poor neighborhoods with a higher percentage of unemployed persons were associated with a higher likelihood of ED visit for ED-PDR and EN-PDR models. Similarly, children living in communities with fewer high school diplomas were found significant for the IP-PDR models. After regular hours treat-and-

release ED visits were associated with higher ED return risk than regular office hour visits. However, days of the hospital visits were not found significant for ED-PDR and IP-PDR models.

Table 5.4: Significant factors associated with preventable ED visits and revisits prediction

Variable	Prediction during enrollment (EN-PDR) Odds ratio (95% CI)	Prediction after ED discharge (ED-PDR) Odds ratio (95% CI)	Prediction after inpatient discharge IP-PDR Odds ratio (95% CI)
Age (y)			
0-5	1 [Reference]	1 [Reference]	1 [Reference]
5-8	1.01 (0.91-1.12), p = 0.54	0.98 (0.94-1.02), p =0.24	1.25 (1.18-1.33), p < 0.01
8-12	1.52 (1.08-2.22), p < 0.01	1.20 (1.16-1.24), p =0.01	1.14 (1.08-1.20), p = 0.01
12-17	1.37 (1.31-1.43), p < 0.01	1.31 (1.28-1.34), p < 0.01	1.57 (1.41-1.69), p < 0.01
Gender			
Male	1 [Reference]	1 [Reference]	1 [Reference]
Female	1.16 (1.03-1.25), p < 0.01	1.09 (1.06-1.12), p < 0.01	0.98 (0.95-1.03), p = 0.23
Race/Ethnicity			
Non-Hispanic White	1 [Reference]	1 [Reference]	1 [Reference]
Non-Hispanic African American	1.50 (1.41-1.61), p < 0.01	1.23 (1.19-1.27), p < 0.01	1.18 (1.12-1.26), p < 0.01
Hispanic	1.25 (1.16-1.34), p <0.01	1.16 (1.13-1.20), p < 0.01	1.04 (0.99-1.09), p = 0.11
Others	1.05 (0.96-1.14), p= 0.12	0.99 (0.95-1.03), p < 0.01	1.03 (0.99-1.08), p = 0.07
Provider density			
High	1 [Reference]	1 [Reference]	1 [Reference]
Low	1.28 (1.16-1.36), p < 0.01	1.20 (1.17-1.23), p < 0.01	1.23 (1.19-1.28), p < 0.01
History of ED visits			
0-1	1 [Reference]	1 [Reference]	1 [Reference]
1-3	1.23 (1.14-1.32), p < 0.01	1.09 (1.04-1.16), p = 0.85	1.89 (1.76-2.11), p < 0.01
>3	1.65 (1.49-1.79), p < 0.01	1.76 (1.35-2.25), p = 0.02	2.40 (2.15-2.65), p < 0.01
% of people with an income below 100% federal poverty level			
1% increment	1.07 (1.03-1.10), p = 0.03	1.06 (1.01-1.11), p = 0.01	0.99 (0.96-1.03), p = 0.61
% of homes with no vehicles			
1% increment	1.01 (0.97-1.05), p = 0.54	0.99 (0.94-1.04), p = 0.46	0.98 (0.93-1.06), p = 0.66
Percentage of the unemployed person			
1% increment	1.06 (1.01-1.11), p < 0.01	1.09 (1.04-1.15), p < 0.01	0.99 (0.95-1.04), p = 0.85
Percentage of people with no high school diploma			
1% increment	1.02 (0.97-1.07), p = 0.29	1.03 (0.98-1.08), p = 0.17	1.03 (1.01-1.06), p = 0.01
Potential health hazards related to family conditions			
1% increment	-	1.06 (1.01-1.12), p =0.04	1.05 (1.01-1.09), p = 0.02
Hospital travel distance			
<20 miles	-	1 [Reference]	1 [Reference]
≥ 20 miles	-	1.78 (1.55-1.93), p < 0.01	1.58 (1.45-1.73), p < 0.01

Table 5.4 (Continued)

ED visit time			
8 am – 6 pm	-	1 [Reference]	-
6 pm – 8 am	-	0.91 (0.84-0.97), p < 0.01	-
Hospital visit days			
Weekdays	-	1 [Reference]	1 [Reference]
Weekends	-	1.02 (0.96-1.06), p = 0.31	1.06 (1.00-1.12), p = 0.06
Physician Referral			
No	-	1 [Reference]	1 [Reference]
Yes	-	1.01 (0.97-1.05), p = 0.19	0.95 (0.91-0.99), p = 0.01
Discharge Disposition			
Routine discharge	-	1 [Reference]	1 [Reference]
Post-acute care	-	3.21 (2.54-4.02), p < 0.01	2.21 (1.78-2.67), p < 0.01
Home-health care	-	0.98 (0.95-1.03), p = 0.58	0.84 (0.71-0.87), p < 0.01
Hospital ownership			
Public /non-profit	-	1 [Reference]	1 [Reference]
For-profit	-	0.96 (0.91-1.01), p = 0.11	0.89 (0.85-0.96), p < 0.01
Hospital Size			
Large	-	1 [Reference]	1 [Reference]
Medium	-	0.92 (0.86-0.98), p = 0.02	0.96 (0.91-1.03), p = 0.76
Small	-	0.98 (0.94-1.02), p = 0.25	0.81 (0.76-0.87), p < 0.01
Hospital type			
Adult	-	1 [Reference]	1 [Reference]
Children	-	0.41 (0.36-0.47), p < 0.01	0.63 (0.55-0.68), p < 0.01
Hospital location			
Rural/micro	-	1 [Reference]	1 [Reference]
Rural/micro	-	1.02 (0.96-1.06), p = 0.49	1.01 (0.97-1.05), p = 0.46
Chronic condition			
Nonchronic	-	1 [Reference]	1 [Reference]
Non-complex	-	1.48 (1.39-1.57), p < 0.01	1.55 (1.46-1.61), p < 0.01
Complex chronic	-	1.85 (1.75-1.95), p < 0.01	2.10 (1.87-2.36), p < 0.01
Inpatient stays			
0-3 days	-	-	1 [Reference]
3-7 days	-	-	1.36 (1.28-1.44), p < 0.01
>7 days	-	-	2.14 (2.02-2.26), p <0.01

5.4 Discussion

Using State of Florida hospital data, our study has three major contributions. First, we proposed a holistic framework of preventable ED visit predictions under managed care settings and, therefore developed and compared several variants of machine-learning-based predictive

models for three prediction models that can improve the overall high-risk patient selection process. Second, we found a substantial proportion of over 50% of the total ED visits that are preventable/avoidable in other care settings. The 30-days preventable pediatric ED revisits rates after Treat-and-Release ED discharge and inpatient care were. The total yearly hospital charges for potentially preventable pediatric ED visits is $1.1 billion, of which $800 million charges for Medicaid managed care covered ED visits. Third, factors associated with the Medicaid preventable ED visits were older age, being discharged to a post-acute facility, hospitalized in non-children's hospitals, presence of complex chronic conditions, longer hospital distance, and living in the historically poor and disadvantaged communities. Therefore, this study comprehensively highlights managed care program's potential to reduce avoidable pediatric ED visits through comprehensive machine learning-based predictive models and provides important insights regarding the influencing factors of preventable ED visits and economic impact in the Florida State Medicaid program.

In this large multicenter study across 265 Florida hospitals, our developed preventable ED visits prediction models showed moderate prediction performance except for the EN-PDR model. To our knowledge, this is the first study to develop and apply machine-learning algorithms to predict preventable ED visits for three prediction timepoint models under MCO settings. In terms of predictive power, the EN-PDR and IP-PDR models we developed showed comparable results with other published works.[52,86–89] However, most of these models considered either adult 30-days ED all-payer revisits or focused on all aged frequent/super ED utilizers and in other country's ED settings, these factors possibly obstruct an equivalent comparison of these models to our proposed models.[52,86,87,90] The lower performance of our proposed EN-PDR model than other models is likely related to the limited available information during MCO enrollments and similar AUC

performance was reported in the adult ED visits to model using only patient information.[87] Consequently, the IP-PDR ED revisits model in our study showed slightly higher discrimination compared with ED-PDR models and suggests the availability of more detailed diagnosis and other information during inpatient hospitalization. During an administrative claim process, only ten diagnoses were reported during ED visits, while thirty diagnoses were reported for inpatient care discharge claims.[91,92]

The overall preventable ED visits rate, ED revisit rates after Treat-and-release ED discharge we found in Florida residents was slightly higher than the prior single-center, dedicated pediatric, and multicenter studies of the published literature to date.[33,52,54,60,66,67,93] This higher preventable ED visits and revisits reported in our study can be explained by multifactorial causes; (1) inclusion of only Medicaid patient population with prior studies, [52,86–89] (2) a higher percentage of non-Hispanic and African American children, (3) a higher degree of pediatric regionalization in Florida compared with other states.[94] Consequently, we found increased readmission risk associated with African American and Hispanic children similar to prior studies.[40,41,95] Children with historically disadvantaged attributes are less likely to have access to primary care or other health care provider that could help to maintain children's health after ED or inpatient care discharge.[96,97] The language barrier may contribute to poorer healthcare access and adverse health outcomes for Hispanic/ Latino children particularly those living in households with limited English proficiency.[98,99] Consequently, parent’s health literacy substantially affects children's ED utilization, and health literacy among the minority raced population is comparably lower than other races and commercially insured patient population.[93,100,101] Besides, a significant association between community-level SDHs (e.g., poor neighborhood and employment rate) and increased risk of preventable ED visits suggests systemic disparities due to socioeconomic inequality.[102,103]

Moreover, increased likelihood of readmission with children living with longer travel distances and children in underserved communities suggest residents in these areas may have limited access to pediatric care due to geographical location.[104,105] Unequal access to health services and quality care is likely to impact children's overall well-being and development health, consequently, increase the occurrence of unwanted health outcomes (e.g. repeated ED visits). Interventions addressing social health determinants and disparities in pediatric care access under MCO setting such as need-based assistance programs, promoting health literacy, early childhood screening, and community-based care can help to reduce overdependence and, thus contribute to reducing unwanted healthcare expenditures.[33,59–61,106]

Our study offers critical insights into the frequency and economic impact of preventable ED visits and suggests opportunities for Medicaid and private managed care organizations through improved high-risk patient selection and implementing comprehensive interventions. One of the potential areas of interventions could be post-acute care discharges and target pediatric care continuity after a hospital visit. In the study, we found a significant association of history of ED visits, complex chronic condition, and non-acute post-discharge with increased risk of readmission, which is consistent with previous investigations.[33] The higher likelihood of preventable ED visits associated with these factors suggests an unresolved system issue care transition complications resulting from fragmented care.[107,108] Children with complex chronic conditions often require a heightened complexity of discharge care planning between an array of healthcare providers.[109,110] High-quality discharge planning including timely communication and telehealth service for low acuity conditions can reduce the utilization of avoidable ED care.[111,112] Similarity, Thorough detailed understanding of hospital visits pattern, MCO should implement strategies to engage certain patients through alternative care settings such as Telehealth and home

health care initiative.[113,114] Florida MCOs have broad flexibility to cover services delivered via telehealth and set their requirements and therefore, the findings of our study could help MCOs to design appropriate alternative care settings supporting the vulnerable populations by providing the care they need.[68,115] Finally, Public health authorities should also take initiatives to enhance primary care capacity and provide additional resource and guidance to motivate children to receive care in a suitable primary care setting for low acuity conditions.[116]

This study has several common limitations, most of which are related to a retrospective analysis of administrative claim databases. First, the HCUP database is an administrative claim dataset that uses ICD codes to classify patients' medical diagnoses, procedures, and outcomes. The possibility of coding inaccuracy or incorrect information cannot be dismissed. Second, although our study makes a significant contribution through developing a preventable ED prediction model under Florida state MCO settings, the findings of this study may not be generalizable to other U.S. state or private MCO. Third, our study was not able to include all Medicaid enrolled beneficiaries' information due to data limitations, including these beneficiaries in the EN-PDR model might improve prediction performance. Fourth, we only considered ED revisits for different insurance payers after the ED and inpatient care covered by Medicaid managed care. However, the proportion of heterogeneous insured ED revisit was expected to be low compared with the same insurance ED revisit. Fifth, our research did not include information regarding the parent health literacy, and post-acute care quality, thus, including these factors may have marginally improved prediction performance. Finally, the HCUP dataset does not include the exact amount hospital received from public and private insurance providers, which may overestimate financial implications for the hospitals.

Chapter 6: A Multi-State Decomposition Analysis of Cesarean Rate Variations, Associated Outcomes, And Financial Implications in the United States

Cesarean rates vary widely across the United States (U.S.) states; however, little is known about the causes and implications associated with these variations. The rationale for this study is that an improved understanding of the realities of existing differences in intrastate cesarean rates and associated outcomes is crucial to state policymakers for developing new action plans or restructuring state Medicaid programs with a goal of more comprehensively meeting public health needs. Hence, the objectives of this study were to quantify the contribution that patient and hospital characteristics in explaining the differences across states and investigate the adverse health and economic implications of cesarean variations. Using the Hospital Cost and Utilization Project State Inpatient Databases, this retrospective study included all non-federal hospital births from Wisconsin, Florida, and New York. The risk factors for cesarean delivery were identified using multivariable logistic regression analysis. A non-linear extension of the Oaxaca-Blinder method was used to decompose the contributions of differences in characteristics to cesarean variations between these states. Multivariable linear regression with hospital random factors and robust standard errors were used to determine differences in outcomes associated with these cesarean variations. Overall (46.57–65.45%) of the variation between states could be explained by the variables, and major contributors were patient demographics, previous cesareans, hospital markup ratios, and social determinants of health. Cesarean delivery was significantly associated with higher postpartum readmissions and unplanned emergency department visits, greater lengths of

stay, and hospital costs across all states. Cesarean variations resulted in differences in adverse postnatal outcomes even after adjusting for risk factors and modes of delivery. Although a proportion of variations in cesarean rates can reasonably be expected given the differences in risk factors, the remaining unexplained variations suggest differences in practice patterns and imply potential quality concerns. Since non-clinical factors are likely to play an important role in cesarean variation, we recommend targeted initiatives increasing access to maternal care and improving maternal health literacy. The complete manuscript titled "A multi-state decomposition analysis of cesarean rate variations, associated health outcomes, and financial implications in the United States", under review in the American Journal of Perinatology, which can be found in Appendix F.

Chapter 7: Estimating Impacts of the Florida Mandatory Managed Care (SMMC) Program in Pediatric and Maternal Care Outcomes

7.1 Backgrounds

7.1.1 A Brief History of Managed Care Program

Medicaid in the United States plays a critical role in ensuring health care needs for the 78 million Americans with limited income and resources.[14] Medicaid healthcare programs, is usually joint funded through federal and state budgets, provides healthcare coverage, and helps with healthcare expense for low-income family's children, maternal care, and people with certain disabilities.[117] The federal government generally sets certain minimum eligibility criteria for Medicaid enrollment. However, Each U.S. state also has the flexibility to lower the eligibility limit and allocate scarce resources to populations more in need.[118] Medicaid healthcare expenditures constitute a substantial proportion of the total federal and state budget. In 2018, total Medicaid spending $616 billion (9% of the total federal budget), of which $96 billion and $34 billion were incurred for children and maternal healthcare.[15] In 2018, more than 35.3% of total US children were covered by Medicaid and children's health insurance program.[119,120] Similarity, state-run Medicaid insurance programs finance nearly 50% of all U.S. births and post-natal care.[121]

Although Medicaid comprises a substantial proportion of healthcare expenditures and is expected to increase by almost 6.2% per year, the overall health and wellbeing of the Medicaid beneficiaries have not improved significantly.[15,17] Medicaid beneficiaries have higher rates of hospital usages (e.g., higher ED visits and readmission rates), higher mortality, and longer hospital

stays than commercial insurance. Furthermore, Medicaid beneficiaries expected substantial racial and ethnic disparities in access to care (timely primary/specialist/OB-GYN care), preventive (e.g., pediatric well-care visits and care experiences), and care experience.[18–22] Therefore, the pressure from increasing healthcare expenditure on the state budget and concern about care quality, many States showed significant interest in managed care programs for the Medicaid population during the last decades.[7] Public managed care plans started in the US around in the 1970s under the name of health maintenance organization (HMO) and received its momentum owing to the two bills Balanced Budget Act of 1997 and ACA act of 2010.[7,122,123] Balanced Budget Act expanded the state Medicaid's authority to sought bids form an organization in managing the health of the beneficiaries, while ACA drives the momentum though increasing Medicaid enrollment from the expansion. Consequently, the total percentage of Medicaid managed care enrollee has gone up from 15 percent in 1995 to 69% in 2018.[22,30,118,124] According to Kaiser founder 2019 reports, 40 states used capitated managed care programs to provide healthcare service to the Medicaid beneficiaries. Besides, more than 75% of total Medicaid beneficiaries were enrolled in mandatory managed care programs and this is expected to grow in the future.[14]

7.1.2 Structures of Managed Care Organization

Medicaid managed care organizations (MCO) usually receive capacitated payments from State Medicaid for a certain patient population and responsible for providing health benefits and additional services to their beneficiaries.[29,30] Since, MCOs are sharing most of the financial risk by state-MCO contract and benefits structure, managed care programs are highly incentivized to reduce unwarranted costs such as preventable ED visits, revisits, readmission, and medically unnecessary cesareans while improving the quality of care. MCOs have broad flexibility to cover services delivered via various care settings and generally set their requirements and therefore,

MCOs can immediately implement interventions such as a need-based assistance program or increasing access to primary care to reduce the risk for subsequent adverse health events. Hence, many U.S. states also implementing other MCO initiatives that focus on improving care quality for the disadvantaged population through aligning payment incentives with performance targets.

7.1.3 Mandatory Managed Care in Florida

Florida is the third populous US state with varied rural-urban geographical areas, characterized by the large diverse children population (58.5 % children of color and 31.8% children with Hispanic), higher uninsured and Medicaid coverages, high pediatric care regionalization, and bottom quantile ranking on health indicators.[94,125,126] The Florida State has almost 30 years of experience with managed care in managing health benefits across its Medicaid population. In 1990, Florida started its first non-risk-based case management care program named MediPass program and, consequently began a pilot risk-based managed care program in 2006 for two counties .[127,128] These programs led to significantly lower per capita healthcare expenditures for the enrollees than the other Medicaid programs.[127,128] These promising results in two Florida counties boost overall interest to enroll more vulnerable Medicaid populations through managed care programs across all Florida counties. Consequently, Florida State Legislature passed mandated managed care legislation in 2011 to control overall Medicaid healthcare expenditure and improve quality of care and received federal waiver approval in 2013. Finally, in April 2014 Florida state started to implement mandatory managed care for Medicaid beneficiaries through Statewide Medicaid Managed Care (SMMC) program.[129] most Medicaid eligible beneficiaries including low-income families and their children, dual Medicaid-Medicare eligible enrollees, and people with certain disabilities are required to participate in managed care programs to receive full benefits.[129] The exempt groups from managed care enrollment are women with certain primary care services (e.g.,

family planning and cancer screening), emergency Medicaid for non-American citizens, and children care in pediatric extended care centers.[129] After the implementation SMMC program, the managed care penetration rate experienced a stable growth to 81.8 % in December 2018 from 47% from September 2014.[130,131]

7.1.4 Research Problem and Objectives

Due to the capitulated and performance-based state contract, Medicaid managed care programs have the incentives to provide beneficiaries to improve care access to care and address health determinants and therefore reduce costly unwarranted health events adverse health events and thus control the overall healthcare plan expenditures. Prior studies reported enhanced access to preventive and primary care and reduction of services such as preventable ED visits and inpatient hospitalization.[132–137] Studies also reported a large reduction in preventable hospitalization and inpatient care related to ambulatory care sensitive conditions in Florida and California managed care populations.[7,132,133] In addition, Medicaid managed care was also found effective in reducing ED utilization, particularly reducing racial/ethnic disparity in preventable adults ED visits rates in Florida state.[8,135–137] However, most of these studies are limited to the adult Medicaid population. However, we have limited information about the overall impact of the managed care on pediatric preventable hospital visits, pediatric care fragmentation, and consequences on the persistence of racial/ethnic disparities in pediatric care. Besides, little is known about the impact of SMMC programs on maternal care, particularly, whether managed care programs impacted low-risk cesarean rates and racial/ethnic disparities in postnatal hospital visits.

Florida's Medicaid agency requires MCOs to submit the Healthcare Effectiveness Data, Information Set (HEDIS), and child core set for performance evaluations.[138,139] However, these performance metrics do not comprise measures that evaluate MCO's effort in addressing children's

and maternal care disparities, resulting in higher preventable ED visits and inpatient readmissions.[139–141] The absence of a metric indicates a quality gap regarding the monitoring and knowledge of the health status and disparity of the children and pregnant women currently enrolled in the managed care plan.[140–142] Hence, there is a need to investigate the impact of the implementation of mandatory managed care in Medicaid on pediatric care visits, disparities, and associated adverse health outcomes. Therefore, we sought to answer the following questions. First, what is the impact of mandatory managed care in Florida in reducing adverse outcomes and racial/ethnic disparities in pediatric care? Second, how SMMC program is impacting the low-risk cesarean rates and preventing associated adverse health outcomes in Florida? We hypothesize that SMMC is associated with lower preventable hospital visits and reduced racial/ethnic disparities across the pediatric and maternal population, mainly due to improved access to primary care and other targeted social need-based interventions.

7.2 Materials and Methods

7.2.1 Dataset

We conducted a retrospective observational study of pediatric hospital visits from January 1, 2016, to September 30, 2017, across all Florida's hospitals, using the Hospital Cost and Utilization Project (HCUP) all-payer State ED (SED) visit and State Inpatient Databases (SID). The SED and SID database is an administrative all-payer database including the uninsured database, which is maintained and certified by the Agency for Health Care Research and Quality (AHRQ).[143] The dataset contains patient-level information on demographic characteristics, insurance status, and International Classification of Diseases, Clinical Modification (ICD-9-CM and ICD-10-CM) diagnosis, procedure codes, and patient location from 265 acute care hospitals across 67 Florida counties. Medicaid quarterly market penetration data for Florida counties

obtained from the Medicaid monthly enrollment report published by the Florida Agency for Health Care Administration (AHCA).[130] We calculated the quarterly rate using data from the monthly enrollment data in March, June, September, and December for the respective year.[7,8] Designated medically underserved area (MUA) status and mon-metropolitan county status were determined using the U.S. Health Resources and Services Administration (HRSA) classification.[144]

7.2.2 Study Settings and Population

We conducted retrospective cross-sectional studies for two different patient populations, (1) children aged 0 to 17 and (2) pregnant women covered by Medicaid and commercial insurance coverage. For the children patient population, we excluded all adult patients (>18), residential addresses outside Florida, and observations with any missing records in the variables. The maternal delivery-related cohort for obstetric delivery-related admissions identified from diagnosis and procedure codes using the widely recognized stepwise methodology.[145] Patient discharges with an abortive outcome, stillbirth, residential address outside the state, against medical advice, and in-hospital mortality were excluded from the dataset.

7.2.3 Outcome Variables

Our health outcome variables for pediatric care quality are preventable ED visits, 30-days unplanned ED visits, 30-days unplanned readmission, and non-index readmission rates. Preventable ED visits were classified using the NYU-ED Billing Algorithm developed by the New York University Center for Health and Public Service Research.[71] 30-days ED revisits is defined as the treatment and release of ED utilization for any unplanned or preventable causes occurring within 30 days of index ED or inpatient care discharge using a similar approach as the NYU-ED Billing Algorithm. All-cause readmission was defined as inpatient hospitalization to any Florida hospital within 30 days following discharge of an acute care hospitalization for any unplanned

reason using the previously validated all-cause Pediatric All-Condition Readmission algorithm by the Boston Children Hospital to identify pediatric readmission.[146] Only the first ED revisits and readmission visits within 30 days were considered and subsequent encounters after 30 days from discharge were identified as another index visit. Finally, non-index readmission rates were defined as the proportion of different hospital readmissions (non-index) out of all pediatric readmissions. For the preventable pediatric ED visits, we analyzed ED visits per 100,000 population in each county, while other outcome varies were considered as binary (yes/no) variables. There have been significant racial/ethnic disparities associated with these pediatric care outcomes[79] and have been used as the indicator of quality-of-care in prior studies.[7,8,132–137]

Our primary outcomes for maternal care were low-risk cesarean rates, post-partum preventable ED visits, and postpartum preventable readmissions, and vaginal delivery after cesarean (VBAC) rates. Low-risk cesarean rates were calculated as the percentage of livebirth cesarean deliveries among all obstetric low-risk deliveries. Low-risk deliveries were identified for all terms as singleton, vertex, and live birth deliveries without prior cesarean and without high-risk diagnoses.[147] Postpartum hospital readmission was defined as an admission within 42 days (6 weeks) after the date of delivery admission.[148] Unplanned ED visits were calculated as a binary (yes/no) variable for any return to the ED within 42 days of hospital discharge using the NYU-ED Billing Algorithm. These maternal care health outcomes were used for monitoring the quality of obstetric care and varied disproportionally among the historically disadvantaged race/ethnic mothers.[149–151]

7.2.4 Covariates

Covariates for the pediatric patient cohort were age (0-1, 1–5, 5–10, 11–14, 14–17 years), gender, and comorbidity score. For the pediatric comorbidity variables, we evaluated 27 common

pediatric pathologies[152] and categorized into three patient groups (0–2 [absent], 3–5 [low] and ≥ 6 [high]).[153] Covariates for the obstetric care cohort were age (<18, 18-30, 30-40, >40 years), and comorbidity score. We evaluated 24 common comorbidities and weighted summed to categorize them into three patient groups (0 [lowest risk], 1 or 2, or >2 [highest]).[154] Race and ethnicity were categorized into three groups non-Hispanic white, non-Hispanic Black, and Hispanic for both patient cohorts.

7.2.5 Modeling and Analysis

We used the difference-in-differences (DID) approach to evaluate the impact of the SMMC on pediatric and maternal healthcare quality outcomes. The DID approach is a quasi-experimental design that has been widely used in causal relationships in health care policy research, particularly when randomization is not available.[155–158] We compare the changes in selected pediatric and maternal health outcomes among Medicaid beneficiaries (treatment) and commercially insured population (comparison), before and after the implementation of SMMC. We considered the pre-SMMC period (January 2010 to March 2014) and comparator post-SMMC implementation period from October 2014 to September 2017 excluding the implementation periods of April 2014 to September 2014. We defined disparity in health outcomes of Medicaid enrollees compared with the outcomes of commercially insured patients. Our DID estimation method assumed that trend in health outcomes for commercially insured patients reflect reflects the secular trend in outcomes.[7,8] We performed multivariable linear regression analyses with county and quarter fixed effect and robust SEs to determine health outcome differences between before and after SMMC implementation periods. The pediatric care outcome preventable hospital visits were compared using multivariate regression analysis with a negative binomial distribution and log link family. The DID estimation model for preventable pediatric ED visits is:

$$Y_{ijkl} = \beta_o + \beta_1 Medicaid_{ijkl} + \beta_2 Medicaid_{ijkl} \times PostSMMC_{ijkl} + \gamma_k Race/ethnicity_{ijkl} \times PostSMMC_{ijkl} + qtr_l + county_i + \delta X_{ijkl} + \varepsilon_{ijkl}$$

where, Y_{ijkl} is the number of preventable pediatric ED visits per 100000 children population insurance i, county j, race/ethnic group k and quarter l. $Race/ethnicity_{ijkl}$, $PostSMMC_{ijkl}$ and $Medicaid_{ijkl}$ are the binary (yes/no) indicators for the race/ethnicity (non-Hispanic African American and Hispanic), post SMMC implementation period (quarter 4 2014 to quarter 3 2017), and Medicaid enrollee, respectively. X_{ijkl} represents average patients characteristics for age group, gender, and comorbidity scores for insurance i, county j, race/ethnic group k and quarter l. $county_i$ and qtr_l represent the fixed effect that quarter and county might have with the outcome and therefore, reduce the estimation bias.

To assess the SMMC impact in other categorical outcomes pediatric and maternal outcomes, we used Propensity Score Weighted multivariate logistic regression analysis with log-link binomial families. The DID estimation model for other health outcomes is:

$$logit[prob(Y_{ijkl}) = 1] = \beta_o + propensity_i + \beta_1 Medicaid_i + \beta_2 Medicaid_i \times PostSMMC_i + \gamma_k Race/ethnicity_{ik} \times PostSMMC_i + qtr_l + county_j + \delta X_i + +\varepsilon_{ijkl}$$

where, Y_{ijkl} is the binary (yes/no) indicator for the selected outcome for patient i, county j, race/ethnic group k, and quarter l. $Race/ethnicity_{ik}$, $PostSMMC_i$ and $Medicaid_i$ are the binary (yes/no) indicators for the race/ethnicity, post SMMC implementation period (quarter 4 2014 to quarter 3 2017), and Medicaid enrollee, respectively. X_i represents covariate variables for patient i. For the pediatric care outcomes, covariates are age group, gender, and pediatric comorbidity scores, where covariates for maternal care outcomes are age group, gender, and obstetric comorbidity scores. $propensity_i$ is the propensity score (0-1) for the patient i. A propensity score

is estimated through a multivariate logistic regression model and has been widely adopted by the researcher to balance the characteristics of the treatment and the sample control group.[159–162]

7.3 Results

The analysis included 55.1 million hospital visits by Florida residents from January 1, 2010, to December 31, 2017, of which 35.6 million were Treat-and-release ED encounters and 19.5 million were hospital inpatient care. Among these hospital visits and those that meet our exclusion criteria, our analysis included 7,683,385 pediatric Treat-and-release ED visits, 501,083 pediatric index hospital visits, and 1,749,129 hospital births. Among these pediatric hospital ED visits, 608,851 them (51.7 %) were found potentially preventable if treated in primary care settings. Among these pediatric ED visits, 6,724,190 were index ED visits of which, 5581108 (8.03%) returned to ED within 30 days of initial ED discharges with preventable causes. Consequently, the total number of index pediatric ED visits and index inpatient visits included in our study were. Among the index visits, 41,107 (8.21%) were readmitted within 30 days. Of the 41,107 readmissions, 5,585 (13.57%) were readmitted to non-index hospitals. Among the identified 1,749,129 hospital births after meeting the inclusion criteria, 594,703 (34.01%) were cesarean deliveries for Florida residents. Of these hospital births, 43728 (2.5 %) were readmitted into inpatient care and 68216 (3.9%) were returned to ED care for preventable causes.

7.3.1 Economic analysis

The median pediatric hospital readmission charges were $27920 with an interquartile range ($15347-$57594), and total readmissions-related hospital charges were $2.54 billion. The average hospital charge for potentially preventable pediatric ED visits was $2325, and total preventable ED visits related to hospital charges were $8.9 billion for the combined study period (average yearly $1.1 billion). Among these hospital charges, Medicaid programs were charged for a

substantial \$6.1 billion (68.5%) of pediatric preventable hospital charges. The total hospital charges for cesarean deliveries in Florida during 2010-2017 were \$12.9 billion with average annual hospital charges of \$1.61 billion. Particularly, the annual total hospital charges for Medicaid-insured cesarean delivery was \$819 million for the study period. In addition, the total postpartum readmission and unplanned ED visit charges were \$550 million and \$41 million, respectively.

Table 7.1: Impact of SMMC on pediatric health outcomes and racial/ethnic disparities

Outcomes	Medicaid Odds ratio (95% CI) P value	Medicaid African American Odds ratio (95% CI) P value	Medicaid Hispanic Odds ratio (95% CI) P value
Preventable ED visits	0.89 (0.84-0.94), p < 0.01	0.81 (0.72-0.91), p < 0.01	0.76 (0.61-0.89), p < 0.01
30-days unplanned ED revisits	0.84 (0.74-0.94), p < 0.01	0.86 (0.76-0.96), p =0.02	0.87 (0.77-0.97), p = 0.01
30-days unplanned readmission	0.96 (0.89-1.03), P =0.25	0.91 (0.84-0.97), P =0.02	0.97 (0.89-1.06), P =0.12
Non-index readmission rates	1.02 (0.94-1.09), p =0.47	1.05 (0.96-1.14), p =0.15	0.99 (0.92-1.06), p =0.25

7.3.2 Differences in Pediatric Outcomes After SMMC

The result from the difference in difference method for comparing pediatric outcomes is shown in Table 7.1. The multivariable analysis adjusted for covariates showed a significant decrease (OR, 0.89; CI, 0.84–0.94 p<0.01) in the incidence of pediatric preventable ED visits. Furthermore, children visited after SMMC implementation resulted in a lower likelihood (OR, 0.84; CI, 0.74–0.94 p<0.01) of experiencing a return ED visits compared with the pre SMMC period. However, overall 30-days unplanned pediatric readmission rates no difference (p=0.47) between the two comparator periods. In addition, readmissions to non-index hospital rates as a proxy measure of care fragmentation were also not found significant.

After adjusted for patient's age and comorbidities, SMMC implementation also revealed a substantial racial/ethnic disparities reduction in pediatric preventable hospital visits compared with the commercial insured and white raced children. The likelihood of experiencing a

preventable ED visit in African American (OR, 0.81; CI, 0.72–0.91 p<0.01) and Hispanic (OR, 0.76; CI, 0.61–0.89 p<0.01) raced children insured with Medicaid were significantly reduced relative to the Medicaid insured non-Hispanic children after SMMC implementation when compared with the commercial insurance rates. A similar reduction of racial/ethnic disparities in 30-days unplanned ED revisits for Medicaid African American (OR, 0.86; CI, 0.76–0.96 p=0.02) and Medicaid Hispanic (OR, 0.87; CI, 0.77–0.97 p=0.01) was also reported. In addition, SMMC resulted in a significant reduction in 30-days unplanned readmission rates for the Medicaid African American children (OR, 0.91; CI, 0.84–0.97 p=0.02) discharged from inpatient care, compared with the Medicaid white and commercial insurance patient population.

7.3.3 Differences in Maternal Outcomes Before and After SMMC

The DID estimation results of SMMC implementation on maternal health outcomes are shown in Table 7.2. The multivariable analysis adjusted for covariates showed no difference in Medicaid low-risk cesarean rates (0.29) and vaginal delivery after cesarean (VBAC) rates (p =0.59), compared to the commercially insured patients. Interestingly, SMMC implementation resulted in a slightly lower likelihood of low-risk cesarean (OR, 0.90; CI, 0.84–0.96 p<0.01) and VBAC (OR, 0.91; CI, 0.82–0.99 p=0.04) for Medicaid African American mother, when compared with the white race and commercially insured mothers. SMMC implementation also revealed a reduction in overall Medicaid Postpartum preventable ED revisits (OR, 0.91; CI, 0.83–0.99 p=0.03) and preventable readmissions (OR, 0.89; CI, 0.78–0.97 p=0.02) compared with the commercial insured rates. Besides, SMMC resulted a significant racial/ethnic disparities reduction in Postpartum preventable ED revisits (OR, 0.86; CI, 0.77–0.97 p<0.01) and Medicaid Hispanic (OR, 0.91; CI, 0.84–0.98 p=0.01). All the models satisfied the post-estimation testing criteria.

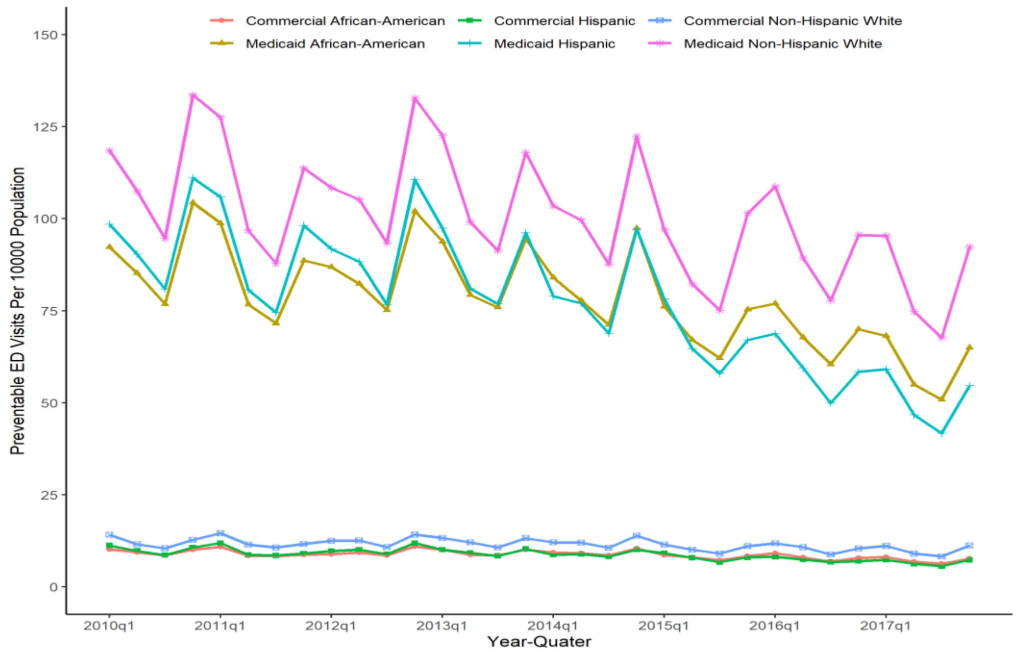

Figure 7.1 Preventable hospital ED visits trends by race/ethnicity and payer

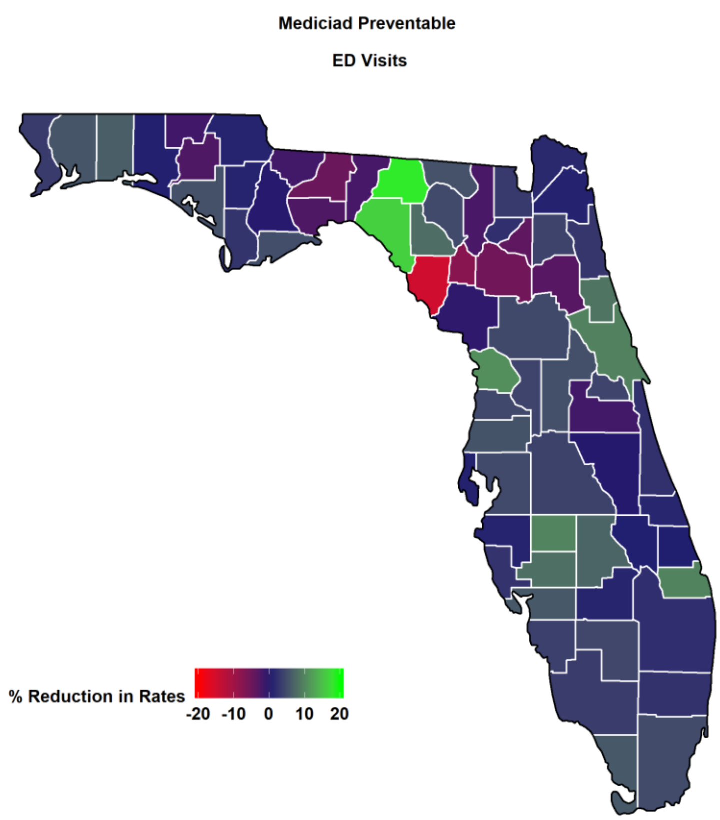

Figure 7.2: Preventable ED visit reduction after SMMC across Florida counties

7.3.4 Regional Variation and Disparities in Underserved Communities

The racial/ethnic disparities in preventable pediatric ED visits and readmission rates are shown in Figure 7.1. The disparities in preventable ED visits showed a slight increase for Medicaid African American and Hispanic children population before the pre-SMMC period and a downward trend compared after quarter 1 2015 compared with the white patient population. We also observed similar upward and downward trends of racial disparities in pediatric readmission rates in both Medicaid and commercially insured patients, compared with the white race population.

Table 7.2: Impact of SMMC on maternal health outcomes and racial/ethnic disparities

Outcomes	Medicaid Odds ratio (95% CI)	Medicaid African American Odds ratio (95% CI)	Medicaid Hispanic Odds ratio (95% CI)
Low-risk cesarean rates	0.97 (0.89-1.05), p = 0.29	0.90 (0.84-0.96), p < 0.01	1.04 (0.96-1.12), p =0.39
Postpartum preventable ED revisits	0.91 (0.83-0.99), p =0.03	0.96 (0.89-1.03), p =0.36	0.86 (0.77-0.97), p < 0.01
Postpartum preventable readmissions	0.89 (0.78-0.97), P =0.02	0.97 (0.89-1.05), P =0.42	0.91 (0.84-0.98), P =0.01
Vaginal delivery after cesarean (VBAC) rates	1.01 (0.94-1.08), p =0.59	0.91 (0.82-0.99), p =0.04	0.99 (0.91-1.07), p =0.16

There was substantial geographic variation in pediatric preventable hospital visit reduction rates across Florida State counties after the implementation of the SMMC program (Figure 7.2). The difference between pre-SMMC and Post-SMMC preventable ED visit rates ranges from 1.2% to 11.3%, while changes in preventable readmission rates range from 0.1% to 8.2% across Florida counties. The average changes in pediatric preventable ED visit rates (4.2% vs 5.9%, p =0.02) and readmission rates (2.1% vs 4.5%, P=0.01) in medically underserved counties were significantly lower than in the other counties. The changes in pediatric unplanned ED revisit rates and non-index readmission rates for medically underserved counties were not found significant compared with other counties. The difference in changes rates in maternal care outcomes for medically underserved counties was also not found significant compared with other counties. Similarly, we

found similar lower SMMC change rates in non-metropolitan counties only for pediatric preventable ED revisits and readmissions rates. Medicaid penetration rates in Florida counties also significantly affected changes in pediatric and maternal outcomes after SMMC implementation. We compared the changes in pediatric and maternal outcomes for two stratified patient groups by counties with a cutoff value of median Medicaid managed care penetrate rates (Table 7.3). We found a slightly higher change in health outcomes for counties with above-median Medicaid managed care penetration rate than other counties. Interestingly, we only found a significant reduction in racial/ethnic disparities for counties with above-median penetration rates than other counties with below-median rates.

Table 7.3: Impact of SMMC on pediatric and maternal care outcomes and racial/ethnic disparities

Outcomes	Counties bellow median SMMC Penetration Rates Odds ratio (95% CI)			Counties over median SMMC Penetration Rates Odds ratio (95% CI)		
	Medicaid	African American	Hispanic	Medicaid	African American	Hispanic
Preventable ED visits	0.91 (0.86-0.96)	0.96 (0.90-1.02)	0.93 (0.86-1.00)	0.86 (0.81-091)	0.79 (0.74-0.85)	0.75 (0.70-0.81)
30-days unplanned ED revisits	0.92 (0.85-0.97)	0.97 (0.92-1.02)	0.96 (0.91-1.03)	0.80 (0.75-0.85)	0.82 (0.77-0.87)	0.86 (0.81-0.91)
30-days unplanned readmission	0.97 (0.82-1.05)	0.99 (0.94-1.06)	0.96 (0.90-1.01)	0.94 (0.87-1.01)	0.89 (0.84-0.94)	0.84 (0.79-0.89)
Non-index readmission rates	1.02 (0.97-1.07)	1.02 (0.96-1.08)	0.99 (0.94-1.04)	0.97 (0.89-1.05)	1.06 (1.01-1.11)	0.96 (0.91-1.01)
Low-risk cesarean rates	1.01 (0.94-1.07)	0.98 (0.92-1.04)	1.01 (0.95-1.07)	0.96 (0.91-1.01)	0.88 (0.81-0.94)	1.01 (0.95-1.07)
Postpartum preventable ED revisits	0.94 (0.88-1.00)	0.99 (0.92-1.05)	0.95 (0.89-1.01)	0.89 (0.84-0.94)	0.95 (0.90-1.01)	0.84 (0.79-0.89)
Postpartum preventable readmissions	0.95 (0.89-1.01)	1.01 (0.96-1.07)	0.91 (0.85-0.96)	0.88 (0.82-0.94)	0.97 (0.92-1.02)	0.92 (0.87-0.97)
VBAC rates	1.01 (0.94-1.07)	0.92 (0.86-0.98)	1.00 (0.94-1.05)	1.01 (0.96-1.06)	0.89 (0.84-0.95)	0.97 (0.92-1.02)

7.4 Discussion

In summary, we investigated the impact of State of Florida mandatory managed care programs in reducing pediatric preventable hospital visits, care fragmentation, and maternal care outcomes, particularly focusing on persistent racial/ethnic disparities. To our knowledge, this is the first study to analyze SMMC's impact on pediatric and maternal care quality and explore the association between SMMC implementation and racial/ethnic disparities. We DID estimation showed evidence of a substantial reduction in several pediatric care outcomes (e.g., preventable hospital visits and revisits) and maternal care outcomes (postpartum revisits and readmission rates) for the Medicaid population compared with the privately insured patient population. After SMMC, historically disadvantaged race/ethnic patients also experienced significantly lower disparities in several pediatric care quality outcomes including preventable ED visits and revisits incidence rates, compared with white and privately insured children. Our results also suggest a significant association with SMMC and lower disparities in maternal care outcomes including postpartum hospital return visits for Medicaid Hispanic patient population and VBAC rates for non-Hispanic African American mothers. Finally, we also estimated the financial impact due to potentially preventable hospital encounters for Medicaid pediatric and obstetric care patient populations. Florida residents with Medicaid coverage resulted in an annual \$1.4 billion and \$73 million hospital charges for preventable pediatric and obstetric care hospital visits, that can be potentially avoidable and could be treated in primary care settings. In general, the study highlights the overall impact of SMMC on pediatric and obstetric healthcare quality in Florida State; and provides important insights regarding the positive dynamics and potential scope for improvement in care quality and associated racial/ethnic disparities among the Medicaid population.

In our study, we found a significant reduction in pediatric ED utilization consistent with the conclusion in several prior studies.[163,164] This reduction in pediatric ED utilization and associated racial/ethnic disparities after SMMC implementation consistent with the adult Medicaid population in Florida.[8] Besides, several studies in other states and other settings also reported ED utilization reduction in various mandatory managed care patient groups.[165–169] This overall reduction in pediatric ED utilization and racial/ethnic disparities reported in our study can be explained by multifactorial causes; (1) higher number of pediatric good care and preventive care visits in recent years[170–172] (2) many managed care organizations implemented effective intervention strategies such as need-based assistance program[173–175] (3) Improved access to more primary care physicians and pediatricians within MCO network for the vulnerable population, due to higher market competition.[176,177] Our findings of similar readmission rate and non-index readmission rates after SMMC may be associated with the prevalence of an increasing number of admissions for children with medical complexities[178] and a higher degree of pediatric regionalization in Florida compared with other states.[94] Although, SMMC resulted in a marginal decline in ED utilization diabetes, there is still the difference in incident rate compared with white and commercially insured children, which suggest they still exist systematic disparities in Medicaid population. Therefore, appropriate interventions addressing social health determinants and disparities in pediatric care such as need-based assistance programs, promoting parent health literacy, early childhood screening, and community-based care can help to mitigate the risk of adverse health outcomes and, thus contribute to reducing unwanted healthcare expenditures.[179–182]

In addition, the reduction in postpartum hospital utilization after SMMC implementation consistent with obstetric outcomes reported in prior managed care cohorts.[183–185] The decline in post-partum readmission rates after SMMC suggests improvement in post-natal primary care

access, better hospital discharge, and care continuity after birth.[186–188] Although, SMMC resulted in an overall reduction in a post-partum preventable hospital visit, disparities in African-Americans were not found significant and therefore suggest reinforce the need for more targeted interventions addressing the persistence of racial/ethnic disparities in obstetric care and birth outcomes. The significant reduction in post-partum preventable hospital visit disparities for the Hispanic patient population is likely related to recent managed care efforts in improving the language barrier for Hispanic/ Latino mothers.[189] The language barrier may contribute to poorer healthcare access and adverse health outcomes for Hispanic/ Latino mother particularly living in households with limited English proficiency.[190–193] Our finding of similar low-risk cesarean rates after SMMC suggests the persistence of cultural differences, patient preferences, and attitudes towards the mode of delivery.[194,195] Additionally, the prevalence of higher cesarean inclined demographic subgroups (e.g., Latin Americans and West Indian Americans in Florida) may contribute to the similar increased cesarean rate among Hispanic mothers.[196,197] Therefore, implementing high-risk population-specific nonclinical interventions, such as midwife/doula-led continuity of care, antenatal education, and training for patients with low-risk pregnancies, through Medicaid programs can significantly reduce the low-risk cesarean rate and other potential adverse birth outcomes.[198,199]

The findings of our study are particularly important since SMMC MCOs reported a substantial financial loss of $550 million throughout the 5-year contracts.[200] Hence, it is critical for all stakeholders including state government, MCOs, and relevant stakeholders to understand the impact of SMMC on the quality of care and understand the opportunities for improvements. Consequently, our study offers critical insights into the pediatric and maternal care quality after the implementation of SMMC in Florida and, therefore, suggests opportunities for both MCOs and

policymakers to improve the overall quality of care and reduce avoidable healthcare expenditures. The similar rates of preventable readmission in both pediatric and maternal care suggest an unresolved system issue care transition complications resulting from fragmented care.[107,108]Through understanding of SMMC impact pattern, MCO could implement strategies to engage certain patients through alternative care settings such as Telehealth and home health care initiative.[113,114] Florida MCOs have broad flexibility to cover services and set their requirements and therefore, the findings of our study could help MCOs to design appropriate alternative care settings supporting the vulnerable populations by providing the care they need.[68,115]

7.5 Conclusions and future works

This study has several common limitations, most of which are related to a retrospective analysis of administrative claim databases. First, the HCUP database is an administrative claim dataset that uses ICD codes to classify patients' medical diagnoses, procedures, and outcomes. The possibility of coding inaccuracy or incorrect information cannot be dismissed. Second, although our study makes a significant contribution through developing a preventable ED prediction model under Florida state MCO settings, the findings of this study may not be generalizable to other U.S. state MCO. Third, the HCUP dataset does not include information for federal hospital discharges and non-hospital births (e.g., birth center deliveries and home births). However, the proportion of these out-of-hospital births are very small compared to hospital births and would not affect our estimation.[201] Fourth, we only considered ED revisits for different insurance payers after the ED and inpatient care covered by Medicaid managed care. However, the proportion of heterogeneous insured ED revisit was expected to be low compared with the same insurance ED revisit. Fifth, our research did not include information regarding health literacy, and post-acute care quality, thus, including these factors may have marginally improved prediction performance. Finally, the

HCUP dataset does not include the exact amount hospital received from public and private insurance providers, which may overestimate financial implications for the managed care. Future research could be directed towards SMMC's impact on children and pregnancy well-care visits to better understand the holistic impact of mandatory managed care in Florida.

Chapter 8: Conclusions and Future Directions

Healthcare delivery systems in the United States is by far one of the most complex in the world with fragile interconnections and linkage between the components of multihospital systems, physician groups, insurers, regulatory organizations, and others. This complexity of care delivery coupled with the shortage of care providers and persistent disparities in care access are often responsible for distortional adverse health outcomes and unnecessary resource utilization in vulnerable Medicaid populations including children and pregnant women. Therefore, the objective of this dissertation is to discover new knowledge regarding care fragmentation and disparities in pediatric and maternal care and develop improved data-informed holistic decision support considering all major Medicaid stakeholders (patient, managed care programs, providers, and state policymakers) that could aid stakeholders in their capacity to better design a more effective and comprehensive maternal and pediatric care delivery. Hence, I explored three knowledge discovery studies and three novel predictive modeling studies to address the research objectives/questions, which can be summarized into the following major findings.

1. A substantial proportion of children experienced non-index readmission and worse health outcomes compared to children who experienced index readmission. Significant factors associated with non-index readmissions were demographic, clinical, discharge planning, and hospital characteristics. Strategies for improving continuity of care by targeting children at high risk for non-index readmissions are necessary to reduce poorer health outcomes.

2. Proposed condition-specific machine-learning methods in chapter 2 improved the readmission prediction in most pediatric conditions compared with the traditional all-cause readmission models. Significant risk factors varied widely by index diagnosis, indicating disease-specific multifaceted intervention plans may help to reduce adverse pediatric outcomes.
3. In chapter 4, proposed a novel early pediatric readmission risk prediction model at the time of hospital admission comparable performance with the traditional at-discharge model. This proposed model can improve the overall high-risk patient selection process for the admitting hospitals since a substantial proportion of pediatric readmission occurred within the first week.
4. In chapter 5, the proposed new high-risk patient selection framework under Medicaid managed care settings achieved moderate discrimination power in predicting pediatric preventable ED visits. After analyzing Florida hospital's data, a substantial proportion (over 50%) of the total ED visits were found preventable/avoidable in other care settings. The total yearly hospital charges for potentially preventable pediatric ED visits in Florida is $1.1 billion, of which $800 million charges for Medicaid-managed care covered ED visits.
5. To better understand the causes of the persistent high variation in interstate cesarean rates, I proposed a non-linear extension of the Oaxaca-Blinder decomposition method. Our approach explained overall (~46.57–65.45%) the cesarean variations across states and which is considerably higher than those of a prior study (~30.7–43.7%) in the United States. Significant factors found in the analysis associated with cesarean delivery across states were socio-demographic (non-White, older age, private insurance, higher

socioeconomic status), clinical (higher comorbidity score), and related hospital characteristics (teaching hospital, larger hospital, higher markup ratio). This study can help managed care programs and state policymakers to devise more effective non-clinical interventions such as including improving access to maternal care, training for patients with low-risk pregnancies for state-specific high-risk groups (e.g., Hispanic/Latino), and restructuring the reimbursement schemes of for-profit hospitals (e.g., bundled payment, managed care).

Finally, the investigation of the impact of SMMC programs is the first study to analyze SMMC's impact on pediatric and maternal care quality and explore the association in reducing racial/ethnic disparities. The estimation showed evidence of a substantial reduction in several pediatric care outcomes (e.g., preventable hospital visits and revisits) and maternal care outcomes (postpartum revisits and readmission rates) for the Medicaid population compared with the privately insured patient population. After SMMC, historically disadvantaged race/ethnic patients also experienced significantly lower disparities in some pediatric and maternal care quality outcomes, while other quality outcomes remained the same as before. This study, therefore, provides important insights for State policymakers regarding the positive dynamics and potential scope for improvement in care quality and associated racial/ethnic disparities among the Medicaid population.

Therefore, in summary, this dissertation comprehensively provides novel insights and introduces innovative decision support approaches that can contribute to multiple Medicaid stakeholders which can be used to improve pediatric and maternal care quality and, consequently, reduce avoidable healthcare expenditures.

There are still several challenges in preventing adverse health outcomes in children and maternal care among the Medicaid population. Future research could be directed towards the development decision support system for designing multifaced intervention programs for high-risk children and pregnancy. Besides, understanding the impact of non-clinical interventions such as health literacy and parents' language barriers among children requires further analysis and how to engage physicians/ hospital staff could engage with parents in these non-clinical interventions need to be addressed. In addition, the COVID-19 pandemic disproportionally affected the Medicaid-insured children and mother health and led to an unprecedented reduction in Medicaid-covered pediatric and maternal hospital visits in Florida, which may short- and long-term adverse impacts on overall health. Therefore, the future direction could be directed to analyze the impact of the COVID-19 pandemic on the Medicaid population and how the situation can be improved through intervention and improve data-driven decision support system.

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Appendix A: Information About the Appendices

Appendices B includes copyright authorizations for the published materials in the Hospital Pediatrics Journal. Appendices D, E and F present paper under review.

Appendix B: Copyright Permission for Published Materials in Appendix C

Hospital Pediatrics - Copyright authorization to use an article on doctoral dissertation

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From: Hasan Symum <hsymum@usf.edu>
Sent: Wednesday, May 26, 2021 1:13 PM
To: Editorial, Hospital Pediatrics <HPedsEditorial@aap.org>
Subject: Hospital Pediatrics - Copyright authorization to use an article on doctoral dissertation

MS ID#: HOSPPEDS/2020/005231
MS TITLE: Characteristics and Outcomes of Pediatric Non-index Readmission: Evidence from Florida Hospitals

Dear Editors,

Good afternoon. My name is Hasan Symum, doctoral candidate at the University of South Florida. We, (myself, and my doctoral adviser) submitted a manuscript [MS ID#: HOSPPEDS/2020/005231], titled “Characteristics and Outcomes of Pediatric Non-index Readmission: Evidence from Florida Hospitals”. Currently, this manuscript has been provisionally accepted with a minor revision and we are planning to submit the revised manuscript within this week.

I would like to include the manuscript materials in my doctoral dissertation. Hence, I want to formally ask for permission to use this material as an appendix for my doctoral dissertation.

I look forward to hearing from you soon.

Best regards
Hasan

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Appendix C: Characteristics and Outcomes of Pediatric Non-Index Readmission: Evidence from Florida Hospitals

Appendix C shows the manuscript titled, " Characteristics and outcomes of pediatric non-index readmission: Evidence from Florida hospitals ", which is accepted and currently in Press in Hospital Pediatrics Journal.

Characteristics and Outcomes of Pediatric Non-index Readmission: Evidence from Florida Hospitals

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Abstract

Objectives: Increasing pediatric care regionalization may inadvertently fragment care if children are readmitted to a different (non-index) hospital rather than the discharge (index) hospital. Therefore, this study aimed to assess trends in pediatric non-index readmission rates, examine the risk factors, and determine whether this destination difference affects readmission outcomes.

Methods: This retrospective cohort study uses the Healthcare Cost and Utilization Project State Inpatient Database to include pediatric (0-18 years) admissions from 2010 to 2017 across Florida hospitals. Risk factors of non-index readmissions were identified using logistic regression analyses. The differences in outcomes between index vs. non-index readmissions were compared for in-hospital mortality, morbidity, hospital cost, length of stay, AMA discharges, and subsequent hospital visits using generalized linear regression models.

Result: Among total 41,107 identified readmissions, 5,585 (13.6%) were readmitted to non-index hospitals. Adjusted non-index readmission rate increased from 13.3% in 2010 to 15.4% in 2017. Patients in the non-index readmissions group were more likely to be adolescents, living in poor neighborhoods, have higher comorbidity scores, traveling longer distances, and discharged at the post-acute facility. After risk adjusting, no difference in in-hospital mortality was found, but morbidity was 13% higher, and following unplanned ED visits were 28% higher among patients with non-index readmissions. Length of stay, hospital costs, and against medical advice discharges were also significantly higher for non-index readmissions.

Conclusions: A substantial proportion of children experienced non-index readmissions and relatively poorer health outcomes compared to index readmission. Targeted strategies for improving continuity of care are necessary to improve readmission outcomes.

Introduction

The readmission rate has become an important metric to assess patient care quality for clinicians, insurers, and healthcare providers.[1] Unplanned hospital readmissions are costly and often associated with adverse health outcomes and therefore have become a major policy concern.[2–4] To combat this, federal and several state governments implemented readmission reduction initiatives and thus incentivized healthcare providers to develop internal strategies to reduce readmissions.[5] As a result, these efforts resulted in a reduction in unplanned readmissions, particularly for targeted adult populations.[6,7] However, pediatric readmission rates remained unchanged and, one study even reported a national increment (8.2%) between 2010 and 2016.[8,9] This lack of change in pediatric readmission despite significant national efforts potentially related to the challenge of determining readmission preventability and applicability of effective interventions to a heterogeneous pediatric population, which reinforces the need for more targeted readmission reduction efforts.[10–12] One of the aspects of preventing pediatric readmissions through targeted interventions could be focusing on care fragmentation risk through the context of readmission to hospital destination.[13] Readmissions to different (i.e. non-index) hospitals comprise a significant proportion (~13%–38%) of total readmissions depending on the patient cohort.[14–16]

Readmissions to non-index hospitals may result in fragmented care due to the inadequate exchange of health information and poor transitions of care among the different health care providers.[17,18] Fragmented care may be particularly problematic for pediatric patients who often require the care of an array of healthcare providers and can lead to worse outcomes.[19] Previous studies have found that readmissions to non-index hospitals were associated with increased mortality, morbidity, length of stay (LOS), and hospital costs.[17,18,20–22] However, the research thus far has been mostly limited to adult populations. Only one study examined pediatric non-index readmission and highlighted the differential importance of the non-index readmission on the hospital readmission performance and anticipated penalties.[23] The study also showed promise in identifying risk factors for the New York hospitals and only limited to patient and hospital-level variables. We have limited information about the trends of this type of fragmentation among pediatric patients, regional variation, what the influencing social factors are, and the clinical and financial consequences.

Therefore, this study aims to quantify the rates, risk factors, geographical variation, and implications of pediatric readmission to non-index hospitals compared to index hospitals. Understanding the pattern of pediatric readmission, particularly in the context of fragmented care (i.e., index vs. non-index readmission), and its impact on outcomes is important for multiple reasons. First, regionalization of pediatric care and pediatric readmission rate has been increased over time, therefore, fragmented care in this context may increase the risk of medical errors, unnecessary tests, and complications.[24,25] Second, understanding the realities of existing pediatric care fragmentation is also crucial for healthcare providers policymakers to develop new action plans aimed at more comprehensive care and improving care continuity.[26] The objectives of this study were to examine the frequency of pediatric non-index readmission in recent years, to explore the regional rural-urban disparities and influential risk factors, and to investigate whether children who are readmitted experienced different outcomes based on hospital destination.

Methods

Study Design

We analyzed the Healthcare Cost and Utilization Project (HCUP) State Inpatient Database (SID) for the state of Florida for the period 2010–2017.[27] We excluded all adult patients (>18), residential addresses outside Florida, discharges against medical advice (AMA), and cases of in-hospital mortality from the dataset. Data on hospitals, including geo-locations, were obtained from the American Hospital Association annual survey. Data on patients' living community conditions were derived from American Community Survey data by linking patients' ZIP codes through Uniform Data System Mapper, a free, publicly available resource developed with the support of the U.S. Health Resources and Services Administration.[28] HCUP SID and other national databases are considered limited datasets, as determined by the local Institutional Review (IRB) Board and IRB approval was therefore not required.

We also used HCUP Nationwide Readmissions Database (NRD) for the period 2010–2017 to confirm our findings regarding pediatric non-index readmission trends. NRD databases were not designed to examine regional variation and do not include patient ethnicity or zip location thus preventing the inclusion of social determinants and travel distance in the risk-factor analysis. Therefore, NRD databases were only used to analyze the non-index readmission trends for 2010-2017 and compared with HCUP Florida SID results.

Variables

Pediatric readmission was defined as the inpatient hospitalization for any unplanned cause (i.e., all-cause) occurring within 30 days of discharge from the index admission. We excluded readmissions for planned procedures and chemotherapy using the pediatric all-condition readmission measure.[29] Our study considered only readmission events that occur in children younger than 18 years. Demographic variables included in our study are age, race, and gender. The other patient factors are payer information (public fee for service, Medicaid managed care, private, and uninsured), inpatient LOS (0–3, 3–8, and ≥ 8 days), and discharge planning (routine, post-acute facility, and home health care). Post-acute facilities in our study were defined if the patient was discharged/ transferred to a skilled nursing, intermediate care, and another type of facility (e.g., Rehabilitation). Hospital-level covariates are children's hospital status, location, ownership status, and bed size. For the comorbidity variables, we evaluated 27 common pediatric pathologies and then weighted summed to generate a pediatric comorbidity score.[30,31]

Travel distances between patients' residences and discharge hospitals were calculated by geocoding using geographical information software.[16,32] Social determinants of health (SDH) variables were the percentage of people with an income below 100% federal poverty level and the percentage of homes with no vehicles. These variables are available at the ZIP code tabulation area level from the U.S. Census survey.[33] Non-metropolitan and metropolitan county status were determined using the non-metropolitan classification.[34] Our outcome variables are in-hospital mortality, morbidity, LOS, hospital cost, AMA discharge, and 30-day unplanned ED visit. We used ICD codes to identify the presence of morbidity as a binary variable. Hospital costs were estimated as the product of hospital charges and the cost-to-charge ratio adjusted for the yearly inflation rate.[35] Thirty-day unplanned ED visits were calculated as binary variable as any return to the ED within 30 days of discharge from index admission.

Statistical Analysis

All 30-day unplanned pediatric readmissions were categorized into two groups, index, and non-index readmissions. Index readmissions occurred when patients were readmitted to the discharging hospital; all other readmissions were non-index readmissions. Patients who were transferred to an index hospital after interfacility transfer were included as index readmissions. To deal with missing values, multiple imputations were conducted using the chained equation for the race variable (<1.5% missing). Bivariate descriptive analyses were performed to compare differences in characteristics between the index and non-index readmission groups. Wilcoxon rank-sum and chi-square tests were used to compare the continuous and categorical variables between the two groups. Multivariate logistic regression with robust standard errors (SEs) was used to identify factors responsible for readmissions to non-index hospitals. The trends of non-index readmission rates were computed by fitting a mixed-effect logistic regression model with the fixed effect for patient-level variables and a random intercept for each hospital.

We performed multivariable linear regression analyses with hospital random factors and robust SEs to determine adjusted health outcome differences between the index and non-index readmissions. The categorical outcomes in-hospital mortality, morbidity, AMA discharges, and 30-day unplanned ED visits were compared using multivariate logistic regression analysis with a separate model for each outcome. Generalized linear models with log-link exponential families were used to assess the differences in hospital costs and LOS. All variables listed above, and the readmission type were included in the regression models. A modified Hosmer–Lemeshow test, a Pearson chi-square test, and pseudo R^2 were used to check the goodness of fit for each model.[36] All statistical analyses were performed using R studio, and a two-sided p-value less than 0.05 was considered statistically significant.

Results

The analysis included 501,083 index hospital visits by 318,762 pediatric patients from January 1, 2010, to September 30, 2017. Among the index visits who met the inclusion criteria, 41,107 (8.2%) were readmitted within 30 days. Of the 41,107 readmissions, 5,585 (13.6%) were readmitted to non-index hospitals. Table-1 summarizes the patient and hospital characteristics for the overall, index, and non-index hospital readmissions. The majority of pediatric readmission were related to adolescents, public health insurance, adult hospitals, and urban large hospitals discharges. The in-hospital mortality and morbidity rates for the readmissions were 0.9% and 14.8%, respectively. The median hospital readmission cost was $8591, and total readmissions-related hospital costs were $817 million. The most frequent pathologies of readmissions include asthma, sepsis, infections, dehydration, and cerebral palsy (Supplemental Table-1).

Geographic variation and trends of non-index readmissions

There was substantial geographic variation in readmission rates for non-index hospitals across Florida (Figure 1). The proportion of non-index readmissions in non-metropolitan counties (mean [SD], 20.9 [10.1]) was significantly greater (p=0.02) than that in metropolitan counties (16.2 [6.6]) throughout the state. The unadjusted rate of patients readmitted to non-index hospitals began to increase as travel distance increased beyond 20 miles (Supplemental Figure 1). We found that the unadjusted non-index pediatric readmission rate decreased from 14.6% to 12.6%. However, the adjusted non-index readmission rate increased from 13.3% in 2010 to 15.4% in 2017 (Figure 1). Using the HCUP NRD data, the national non-index readmission rates revealed a similar trend (adjusted national rates increased from 13.6% in 2010 to 14.5% in 2017) compared with Florida estimates (Supplemental Table-2).

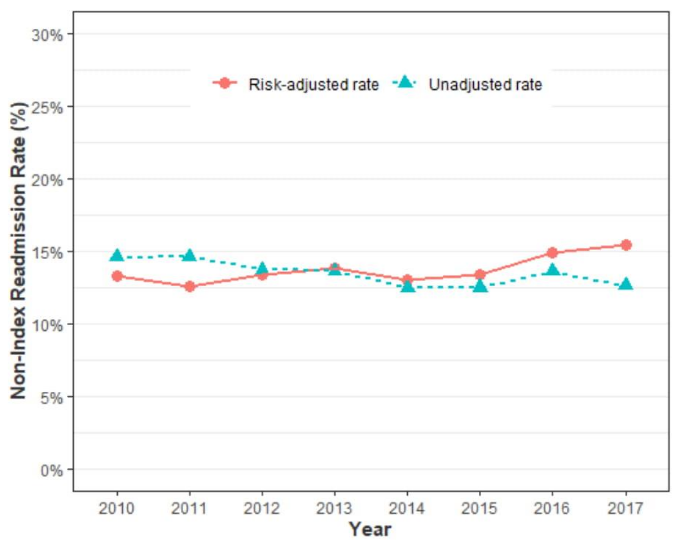

Figure 1: Trends in 30-day pediatric non-index readmission rates

Table 1. Patient and hospital characteristics for the overall, index and non-index 30-day readmissions

Variable	**Total (N=41107) n (%)**	**Index readmission (n = 35522) n (%)**	**Non-index readmission (n = 5585) n (%)**	**P value**
Age (y)				
0-1	5762 (14.0)	5148 (14.5)	614 (11.0)	<0.001
1-5	8966 (21.8)	7985 (22.5)	981 (17.5)	
5-8	3961 (9.6)	3500 (9.8)	461 (8.3)	
8-12	5270 (12.8)	4703 (13.2)	567 (10.2)	
12-17	17148 (41.8)	14186 (40.0)	2962 (53.0)	
Gender				
Male	20893 (50.8)	18134 (51.1)	2759 (49.4)	0.12
Female	20214 (49.2)	17388 (49.9)	2826 (50.4)	
Race				
White	16268 (39.6)	13842 (40.0)	2426 (42.9)	<0.01
African American	13095 (31.8)	11370 (31.8)	1725 (30.6)	
Hispanic/Latin	9974 (24.2)	8780 (24.6)	1194 (20.9)	
Others	1770 (4.3)	1530 (4.4)	240 (4.3)	
Missing	270 (0.7)	195 (0.5)	75 (1.3)	
Insurance				
Public FFS[1]	16964 (41.3)	14783 (41.6)	2181 (39.1)	<0.01
Medicaid MCO[2]	13084 (31.8)	11227 (31.7)	1857 (33.2)	

Private	8826 (21.5)	7587 (21.4)	1239 (22.2)	
Uninsured	2233 (5.4)	1925 (5.5)	308 (5.5)	
Distance (home to index hospital)				
<10 miles	14435 (35.1)	12561 (35.3)	1874 (33.5)	<0.001
10-20 miles	11874 (28.9)	10437 (29.4)	1437 (25.7)	
≥ 20 miles	14798 (34.0)	12524 (35.3)	2274 (40.8)	
Discharge disposition				
Routine	35063 (85.3)	32890 (92.5)	2173 (38.9)	<0.001
Post-acute discharge facilities	4344(10.6)	1003 (2.8)	3341 (59.8)	
Home Health care	1700 (4.1)	1629 (4.7)	71 (1.3)	
Length of stay				
0-3 days	21132 (51.4)	18347 (51.6)	2785 (49.9)	<0.001
3-8 days	10803 (26.3)	9497 (26.7)	1306 (23.3)	
≥ 8 days	9172 (22.3)	7678 (21.7)	1494 (26.8)	
Pediatric comorbidity scores				
0-2	24769 (60.2)	21534 (60.6)	3265 (58.5)	<0.01
3-5	8874 (21.6)	7658 (21.5)	1216 (21.8)	
≥6	7464 (18.2)	6360 (17.9)	1104 (19.7)	
Missing	0	0	0	
Percentage of people living below 100 Federal Poverty Limit				
Median (IQR)	18.8 (12.9-25.6)	18.8 (12.8-25.6)	18.5 (13.1 – 25.5)	<0.001
Percentage of home with no vehicles				
Median (IQR)	6.8 (4.1-10.8)	6.8(4.1-11.0)	6.6 (4.0 – 10.3)	<0.01
Hospital type				
Children	9743 (23.7)	8813 (24.8)	930 (16.7)	<0.001
Adult	31364 (76.3)	32294 (75.2)	4655 (83.3)	
Hospital location				
Division	7986 (19.4)	6913 (19.4)	1073 (19.2)	<0.001
Metro	32931 (80.1)	28490 (80.1)	4441 (79.5)	
Micro/Rural	190 (0.5)	119 (0.5)	71 (1.3)	
Hospital ownership				
Non-profit /Government	4962 (12.1)	4340 (12.2)	1017(18.3)	<0.001
For profit	36145 (87.9)	31182 (87.8)	4568 (81.7)	
Hospital Size				
Large	27829 (67.7)	24294 (68.4)	3535 (63.3)	<0.001
Medium	12044 (29.3)	10207 (28.7)	1837 (32.9)	
Small	1234 (3.0)	1021 (2.9)	213 (3.8)	
[1.] Public FFS: Public Fee for Service insurance providers [2]Medicaid MCO: Medicare Managed care Organization				

Index vs. non-index hospital readmissions

The bivariate and multivariate analyses for factors influencing non-index readmission are shown in Table-2. Based on the multivariate analysis, factors that were more likely to be associated with pediatric readmissions to non-index hospitals were older age, being discharged to a post-acute facility, a longer hospital LOS, hospitals located in micro/rural, and smaller hospital bed size. The presence of higher comorbidity scores were also significant predictors of non-index readmission. Living more than 20 miles from the index admission hospital and in areas with higher poverty percentages was associated

with non-index readmissions. Patients with private insurance and living in areas with fewer private vehicles were less likely to be readmitted to non-index hospitals. Moreover, patients who were initially admitted to non-profit and adult hospitals were more likely to be readmitted to different hospitals. However, gender and race were insignificant in the multivariate analysis. The model satisfied the testing criteria based on the modified Hosmer–Lemeshow (p=0.53) and Pearson chi-square (p=0.71) goodness-of-fit tests with 0.12 pseudo R^2.

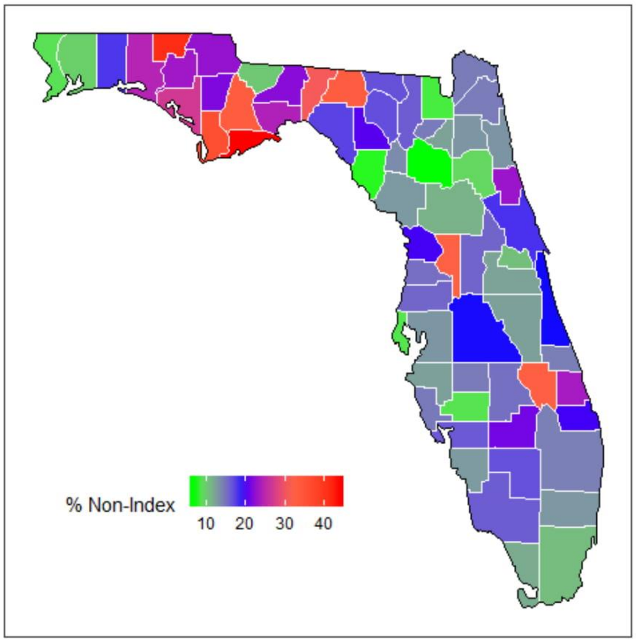

Figure 2: Proportion of Pediatric Readmissions to Non-Index Hospitals to Florida Counties.

Table 2: Factors associated with readmission to non-index hospitals

	Bivariate		**Multivariate**	
Variable	**Odds ratio (95% CI)**	**P value**	**Odds ratio (95% CI)**	**P value**
Age (y)				
0-1	1 [Reference]		1 [Reference]	
1-5	1.03 (0.92, 1.14)	p = 0.58	0.98 (0.88, 1.10)	p =0.80
5-8	1.03 (0.97,1.25),	p= 0.12	1.06 (0.93, 1.21)	p =0.35
8-12	1.01 (0.89,1.14),	p =0.86	0.94 (0.83, 1.07)	p =0.41
12-17	1.75 (1.59, 1.92)	p< 0.001	1.34 (1.22, 1.49)	p < 0.001
Gender				
Male	1 [Reference]		1 [Reference]	
Female	1.04 (0.99, 1.10)	p= 0.09	1.05 (0.99, 1.12)	p = 0.07

Race				
White	1 [Reference]		1 [Reference]	
African American	0.89 (0.83,0.95)	p < 0.01	0.95 (0.86, 1.01)	p =0.22
Hispanic/Latin	0.76 (0.71,0.82)	p <0.001	0.92 (0.85, 0.99)	p =0.03
Others	0.90 (0.77,1.03),	p= 0.15	0.94 (0.81, 1.10)	p=0.50
Travel distance (home to index hospital)				
<10 miles	1 [Reference]		1 [Reference]	
10-20 miles	1.04 (0.94,1.16)	p =0.09	1.09 (1.02, 1.18)	p < 0.01
≥ 20 miles	1.21 (1.13,1.30)	p<0.001	1.60 (1.49, 2.74)	p < 0.001
Disposition				
Routine	1 [Reference]		1 [Reference]	
Post-acute discharge facilities	4.25 (3.26, 5.42)	p <0.001	3.19 (2.64,4.21)	p < 0.001
Home Health care	0.88 (0.75, 1.02)	p = 0.10	0.82 (0.70, 0.95)	p < 0.01
Length of Stay				
0-3 days	1 [Reference]		1 [Reference]	
3-8 days	0.90 (0.84, 0.97)	p =0.03	0.95 (0.88, 1.04)	p =0.10
≥ 8 days	1.28 (1.19, 1.37)	p < 0.001	1.15(1.04, 1.31)	p <0.001
Insurance				
Public FFS[1]	1 [Reference]		1 [Reference]	
Medicaid MCO[2]	1.10 (1.04, 1.18)	p < 0.01	1.06 (0.99, 1.14)	p=0.06
Private	1.11 (1.03, 1.19)	p < 0.01	0.89 (0.82, 0.97)	p = 0.01
Uninsured	1.08 (0.95, 1.22)	p = 0.23	0.93 (0.81, 1.07)	p = 0.36
Pediatric comorbidity scores				
0-2	1 [Reference]		1 [Reference]	
3-5	1.10 (1.03, 1.18)	p <0.01	1.10 (1.02, 1.19)	p=0.01
≥6	1.16(1.08, 1.24)	p <.001	1.09 (1.01, 1.19)	p=0.03
Hospital location				
Division	1 [Reference]		1 [Reference]	
Metro	1.00 (0.94, 1.07)	p =0.90	0.88 (0.81, 0.96)	p <0.01
Micro/Rural	3.84 (2.83, 5.17)	p < 0.001	2.41 (1.73, 3.33)	p <0.001
Hospital ownership				
For profit	1 [Reference]		1 [Reference]	
Non-profit /Government	0.56 (0.43-0.65)	p< 0.001	1.18 (1.08-1.29)	p < 0.01
Hospital Size				
Large	1 [Reference]		1 [Reference]	
Medium	1.19 (1.12, 1.27)	p < 0.001	3.52 (3.15, 3.94)	p < 0.001
Small	1.37 (1.16, 1.61)	p < 0.01	1.60 (1.32 ,1.93)	p <0.001
Hospital type				
Children	1 [Reference]		1 [Reference]	
Adult	2.13 (1.91, 2.38)	p < 0.001	3.39 (2.46-4.28)	p < 0.001
Percentage of people living below 100 Federal Poverty Limit in the neighborhood				
(5 % Increment)	1.01(0.99,1.02)	p = 0.08	1.04 (1.01, 1.09)	p <0.001
Percentage of home with no vehicles				
(5 % Increment)	0.95 (0.93,0.97)	p < 0.001	0.90 (0.84, 0.95)	p < 0.001

[1.] Public FFS: Public Fee for Service insurance providers
[2]Medicaid MCO: Medicare Managed care Organization

Differences in outcomes between the index and non-index readmissions

The multivariable analysis (Table-3) adjusted for covariates showed no difference in in-hospital mortality between readmissions ($p=0.16$) to non-index hospitals and index hospitals. However, readmissions to non-index hospitals resulted in 13% higher odds of experiencing a morbidity (OR, 1.13; CI, 1.04–1.29 $p<0.01$) and 28% higher odds of a 30-day unplanned ED visit (OR, 1.28; CI,1.18–1.38; $p<0.001$) compared with index hospitals. The overall LOS was longer ($p<0.001$) for non-index readmissions than for index readmissions. Besides, patients readmitted to non-index hospitals had a 3.6 times higher likelihood (OR, 3.65; CI, 2.51–5.31; $p<0.001$) of being discharged AMA than from index hospitals. Hospital costs were slightly higher for non-index readmissions (median cost $9364 vs. $8471; $p=0.04$) than for index readmissions.

Table 3. Outcome differences between readmission to index versus non-index hospitals

Readmission Outcomes	Index Readmission (n=35522)	Non-index readmission (n=5585)	Estimated adjusted rate for non-index readmission	Odd Ratio 95 % confidence Interval	P value
Mortality, No (%)	313 (0.9)	47 (0.8)	0.9	1.01 (0.98-1.04)	0.16
Morbidity, No (%)	5211 (14.7)	861 (15.4)	14.6	1.13 (1.04-1.29)	<0.01
Unplanned ED visits, No (%)	6192 (17.4)	1210 (21.7)	17.6	1.28 (1.18-1.38)	<0.001
Discharges against medical advice, No (%)	81 (0.2)	62 (1.1)	0.03	3.65 (2.51-5.31)	<0.001
Length of stay, median (IQR) days	3 (2-6)	4 (2-8)	3.23	NA	<0.001
Hospital cost, median (IQR) $	8471 (5162-18234)	9364 (4683-17400)	8723	NA	0.04

Discussion

Our study has three salient findings. First, Risk-adjusted non-index readmission rates increased on average by 15.8% from 2010 to 2017. Second, factors associated with non-index readmissions were demographic, clinical, discharge planning, hospital characteristics, and social determinants. Finally, pediatric non-index readmissions were significantly associated with poorer outcomes and increased health care expenditures Overall, the study highlights the persistence of pediatric care fragmentation after the initial hospitalization and provides insights regarding the contributing factors and adverse health implications of these non-index pediatric readmissions.

The increase in adjusted non-index readmission rates over time could be explained by the large degree of increasing pediatric care regionalization coupled with increasing readmission risk among hospitals over time.[8] High-acuity complex conditions often require prompt diagnoses and fast treatment to stabilize the patients. Emergency medical services (EMSs) or parents might prefer to take such high-risk patients to the geographically closest hospital rather than an index one.[14,22] Our finding of higher non-index readmission rates in non-metropolitan counties throughout Florida suggests that residents in these areas have limited access to index hospitals due to geographical location.[15] This inequality of care of access due to geographical location restates the persistence of rural-urban disparities in children's healthcare delivery resulting from the steady decline in the hospitals capable of treating children.[25,37,38] Therefore, targeted community-based programs focusing on reducing disparities in

pediatric care access may help mitigate the risk of the occurrence of unwanted health outcomes in children in these areas.

In addition, we found that patients discharged to post-acute care facilities are almost three times more likely to be admitted to non-index hospitals than patients discharged home. This finding may be associated with the prevalence of potentially preventable care transition problems resulting from the discrepancies in health information exchanges and disrupted coordination among hospitals and post-acute care providers.[39,40] Additionally, a higher frequency of EMS service usage associated with high-acuity patients in post-acute discharge facilities might also contribute higher likelihood of readmission to non-index hospitals. EMS service personnel generally follow strict state/county protocol transporting high acuity patients to the designated hospitals rather than index one. [41–43] Conversely, patients discharged to home care settings are less likely to be readmitted to non-index hospitals. Comprehensive and coordinated care through home health settings can be a more convenient and efficient alternative to care delivered in post-acute facilities, particularly under managed care settings.[44,45] Furthermore, patients discharged from children's and large hospitals tend to be readmitted to index hospitals similar to prior study.[23] This might be related to the steady increase in interfacility transfer (majority were transferred to a children's hospital) resulting from the decline in adult hospital capability in treating complex pediatric conditions. [25,32] Association between community-level SDHs and non-index readmission rates suggests potential disparities in pediatric care access due to socioeconomic inequality which is likely to impact children's well-being and increase the prevalence of adverse health outcomes.[46] Therefore, interventions addressing the SDHs might help to mitigate the potential negative outcomes, particularly for children with unfavorable social circumstances.[47]

Our study showed that non-index readmissions were associated with poorer health outcomes of longer LOS, higher morbidity, higher inpatient costs, and a higher risk of 30-day unplanned ED visits than index readmissions. The possibility of these poorer health outcomes after non-index readmission suggests a potential discontinuity of care after initial discharge.[49–51]. Additionally, we found that the non-index readmission group had a significantly higher risk of AMA discharges than same-hospital readmissions. AMA discharge often exposes patients to the risk of inadequately treated conditions and the associated higher prevalence of subsequent readmission and mortality.[52] Therefore, interventions to improve continuity of care, particularly in the early care transition period, could lower non-index readmissions and thus contribute to reducing healthcare utilization, costs, and adverse health outcomes. [49,53,54] Besides, identifying patients with risk of non-index readmission and adverse health outcomes at the time of discharge, the hospital can assign a dedicated follow-up specialist/nurse and prepare a plan that ensures care continuity and accurate health information exchange among healthcare providers. The difference in in-hospital mortality between the index and non-index readmissions were not found significant, similar to the findings of previous studies.[14,20,48]

Our study has some limitations, most of which are related to the retrospective analysis of administrative datasets. First, HCUP SID is an administrative claim dataset that uses ICD codes, and therefore, the possibility of coding inaccuracy cannot be dismissed. Second, the HCUP dataset only considers hospital admissions within the same state; therefore, our study excluded patients readmitted to out-of-state hospitals. However, the proportion of these patients is presumed to be minimal compared with the in-state patient population owing to the geographic location of Florida State and therefore unlikely to influence our results. Third, our study used a single composite comorbidity score in the risk-adjusted estimation. This might overestimate or underestimate risk for specific individuals and therefore, including individual comorbidities and their complex interaction might improve risk-adjustment estimation. However, studies reported identical performance using a single comorbidity

score when compared with individual comorbid conditions regarding model fit, predictive ability, and effect on inference.[55–57] In addition, our research did not include information regarding the parent health literacy, hospital follow-up plan, and post-acute care quality, thus, including these factors may have marginally improved risk- prediction performance. Finally, our study is limited to pediatric admissions among Florida hospitals; therefore, the findings of our study may not be generalizable to other State pediatric populations. However. a similar national non-index pediatric readmission trend reported in our study using the NRD dataset compared with the Florida SID dataset suggests that state-level findings, particularly non-index readmission trends can be used to approximate national-level findings.

Conclusions

In a novel analysis using Florida state administrative database, this study reported increasing trends of pediatric non-index readmission, associated rural-urban disparities, identified several new risk factors including travel distance and social determinants, and relative poorer outcomes compared with index readmission. Significant rural-urban disparities in non-index readmission across Florida counties highlight the persistent need to improve pediatric care access in the rural and underserved areas. Patients readmitted to non-index hospitals experienced poorer health outcomes than those readmitted to index hospitals, probably because of discontinuity of care. Additionally, the rising trend of risk-adjusted non-index readmission rates over the last few years and the significant geographical variation suggests persistent disparity in care access for many children, especially in rural areas. Relatively poorer outcomes associated with non-index readmission indicate the benefits of continuity of care and reinforce the need for health policies and interventions to improve care communication and information exchange across the healthcare delivery spectrum.[15,24]

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List of Tables and Figures included in the online-only supplement

Supplemental Table 1: Top 10 pathologies of pediatric readmission and associated index vs non index readmission rates .

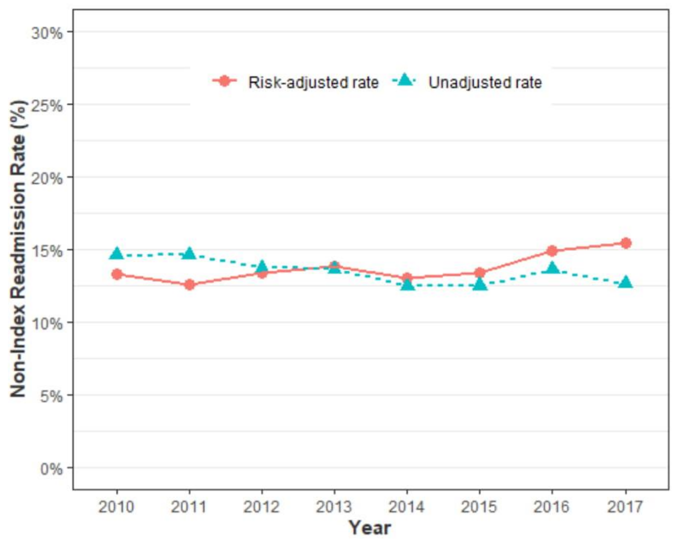
Diagnosis category at readmission	**Total readmissions N= 41107 n (% of total readmission)**	**Total index readmission n (Index readmission rates [%])**	**Total Non-index readmission n (Non-index readmission rates [%])**
Asthma	6786 (16.51%)	5776 (85.12)	1010 (14.88)
Seizure	5653 (13.75%)	4860 (85.97)	793 (14.03)
Septicemia Infection	4751 (11.56%)	4166 (87.69)	585 (12.31)
Dehydration	3823 (9.30%)	3253 (85.09)	570 (14.91)
Cerebral Palsy	2867 (6.97%)	2438 (85.04)	429 (14.96)
Anemia	2859 (6.96%)	2480 (86.74)	379 (13.26)
Pneumonia	2464 (5.99%)	2080 (86.42)	384 (15.58) *
Hydrocephalus	2160 (5.25%)	1870 (86.57)	290 (13.43)
Urine infection	1834 (4.46%)	1563 (85.22)	271 (14.78)
Renal failure	850 (2.07%)	699 (82.24)	151 (17.76) *

* conditions with non-index hospital readmission rates above the overall average of 15%

Supplemental Table 2: Weighted admission characteristics for all pediatric patients admitted between 2010 and 2017 in the NRD dataset

Variable	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Pediatric Index admission								
N	2297777	2078215	2004789	1957428	1924542	19000488	1840833	1813841
Total Readmission								
n (%)	136940 (5.94)	124388 (5.98)	121434 (6.05)	119951 (6.12)	119870 (6.23)	112342 (5.93)	104583 (5.68)	101268 (5.58)
Non-index Readmission								
$n_{noninex}$ (% of n)	20016 (14.61)	18286 (14.71)	17434 (14.36)	17522 (14.60)	15714 (13.11)	14978 (13.33)	13514 (12.92)	13278 (13.16)
Age (y)								
mean (SD)	8.11 (6.76)	7.76 (6.74)	7.70 (6.75)	7.35 (6.72)	7.11 (6.72)	7.09 (6.73)	7.03 (6.77)	7.14 (6.78)
Female								
n (%)	1120300 (48.76)	1005865 (48.40)	970441 (48.40)	942329 (48.14)	920638 (47.84)	909078 (47.84)	874850 (47.53)	860243 (47.42)
Insurance								
Public n (%)	1285707 (55.95)	1129438 (54.34)	1087646 (54.25)	1086041 (55.48)	1067626 (55.47)	1067798 (56.18)	1042046 (56.60)	1042717 (57.48)
Private n (%)	858866 (37.38)	812460 (39.09)	783414 (39.01)	750872 (38.36)	740358 (38.46)	723771 (38.08)	694349 (37.71)	674015 (37.16)
Uninsured n (%)	148595 (6.46)	131180 (6.31)	128580 (6.41)	118678 (6.06)	114115 (5.93)	106710 (5.61)	102416 (5.56)	94680 (5.22)
Pediatric comorbidity scores								
0 n (%)	1787028 (77.77)	1625517 (78.22)	1565062 (78.06)	1509382 (77.11)	1500231 (77.95)	1459471 (56.18)	1406354 (76.40)	1399129 (77.13)
(3-5) n (%)	351146 (15.28)	315621 (15.19)	300799 (15.00)	301940 (15.42)	277660 (14.43)	288048 (15.17)	276931 (15.04)	266236 (14.68)
≥6 n (%)	159603 (6.95)	137077 (6.56)	138927 (6.93)	146106 (7.46)	146650 (7.62)	152968 (8.05)	157548 (8.55)	148476 (8.19)

Supplemental Figure 1: Trends in 30-day pediatric non-index readmission rates



Appendix D: Identifying Children at Readmission Risk: At-Discharge Versus Traditional At-Discharge Readmission Prediction Model

Appendix D shows the manuscript titled, " Identifying Children at readmission Risk: At-admission versus traditional at-discharge readmission prediction model ", which is under review in Journal of Intelligent Systems.

Identifying Children at Readmission Risk: At-admission versus traditional at-discharge readmission prediction model

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Abstract

The timing of the pediatric readmission is highly skewed with approximately 40% of the occurred within seven days. The skewed pediatric distribution coupled with delay in health information exchange between healthcare providers might offer a limited time to the hospital to devise a comprehensive intervention plan. However, Previous pediatric readmission studies are thus far limited to the development of a prediction model after patient hospital discharges. In this study, we propose a novel pediatric readmission prediction model at the time of hospital admission to improve the high-risk patient selection process and compared it with the traditional at-discharge readmission prediction model. Using the Hospital Cost and Utilization Project database, this prognostic study included pediatric hospital discharges in Florida from January 2016 through September 2017. Four machine learning algorithms including logistic regression (LR) with backward stepwise selection, Decision tree (C4.5), Support Vector machines (SVM) with the polynomial kernel, Gradient Boosting (GB) algorithms were developed for at-admission and at-discharge model using a recursive feature elimination technique with a repeated cross-validation process. The performance of the at-admission and at-discharge model was measured by the area under the curve (AUC). The performance of the at-admission model was comparable with the at-discharge model for all four algorithms. SVM with Polynomial Kernel algorithms outperformed all other algorithms for at-admission and at-discharge models. Important features associated with increased readmission risk varied widely across the type of prediction model and were mostly related to patients' demographics, social determinates, clinical factors, and hospital characteristics. Proposed early readmission risk decision support model can help to admitting hospitals and providers additional time for intervention planning, particularly for those targeting social determinants of children's overall health.

Introduction:

Unplanned Hospital readmissions disrupt the daily routine lives of patients and families, expose patients to the risk of hospital-acquired infections and other potentially harmful conditions.[1–3] The 30 days readmission rate has become a critical metric in assessing patient hospital care quality for hospitals and others healthcare providers.[4] Unplanned hospital readmissions are costly and often associated with adverse health outcomes and therefore have become a major policy concern.[5–7] In 2016 national estimates by the Agency of Healthcare Quality (AHRQ), readmissions within 30-days resulted in the in-hospital cost of $2.5 billion for children and $52.4 billion for adults.[8] To combat this, the Centers for Medicare and Medicaid Services (CMS) adopted the Hospital Readmissions Reduction Program (HRRP) in 2012 that penalizes hospitals with higher than expected readmission rates for targeted conditions and thus incentivizes hospitals to develop internal strategies to reduce readmissions.[9] Similarly, many states have begun imposing penalties payments to hospitals and Managed Care Organizations (MCO) with excess Medicaid readmissions rates, particularly for pediatric readmission.[10,11] These efforts resulted in a significant reduction in 30-days unplanned readmissions, particularly for targeted adult populations, one study estimated an 8% reduction in national rates between 2010 and 2015.[12] Compared to pediatric adult and private insured readmission rates, pediatric readmission rates remained unchanged and, one study even reported a national increment (8.2%) between 2010 and 2016.[13,14] Therefore, readmission reduction efforts in pediatric patient population gained significant attention to healthcare providers and professionals more recently in devising ways of reducing readmission risk among children.[15–17] An improved readmission reduction model can help hospitals and healthcare providers to identify high-risk patient groups and therefore, implement interventions in a timely manner that reduce the risk of unplanned admission within 30 days of hospital discharges.

In the last decade with the wide adoption of electronic medical record systems across hospitals and other provider systems, researchers have focused on predictive analytics to identify patients at greater risk of being readmitted and finding ways to prevent unplanned hospital visits.[18–20] Accurate and early prediction of readmission risk prediction provide opportunities for hospitals and insured companies, design and implement direct general or condition-specific interventions toward those who might need most by identifying high-risk patients.[21] Owing to the CMS hospital readmission reduction programs, prediction of adult and Medicare patients have been subject of substantial research and tacked by various hospital admission and readmission timing approaches.[22,23] However, readmission predictions for children have received limited attention.[24,25]

Prior pediatric readmission studies are thus far limited to the development of a prediction model after patient hospital discharges.[26,27] Most of these after-discharge readmission prediction studies reported predictive models for a 30-day readmission and, recently one study showed promise for 7- day pediatric readmission prediction.[28–30] However, these after discharges predictive model application might provide a limited amount of time for hospitals and providers to identify high-risk children and devise any appropriate general or patient intervention plans, mainly due to characteristics and timing of pediatric readmission. Timing of the prediction model application in pediatric hospital care is important for multi-factorial reasons. First, the timing of the pediatric readmission is highly skewed, prior studies reported approximately 40% of the readmission occurred within the first week of hospital discharges.[31] Second, preventing pediatric readmission is often required multi-faceted interventions including clinical and non-clinical (e.g., targeting social determinants of health), which requires participation from both hospitals and healthcare insurers (e.g., MCOs).[15] The skewed pediatric distribution coupled with delay in health information exchange between healthcare providers, might jeopardize multifactorial interventions plan due to time constraints.[32,33] Consequently, strategies for reducing pediatric readmissions need to account

for the higher frequency of readmissions within the first week of discharge, thus warrant an early but similar predictive performance readmission model to better target the high-risk patients and risk-factor for readmission. Therefore, it is crucial to develop an early readmission risk prediction model, that can be coupled more effectively with appropriate intervention programs by improving discharge planning, parent-provider care coordination, and ultimately improve quality of care.[34]
Our study hence aimed to develop prediction models that can better identify those children that are at high risk of unplanned hospital readmission visits. In this study, we propose a novel pediatric readmission prediction model at the time of hospital admission, which we hypothesized would have helped physicians and providers additional time for intervention planning, particularly for those targeting social determinants of children's overall health. In addition, we looked into the predictability performance of our proposed model compared with the existing at discharge model, investigated the performance tradeoff and the optimal timing of implementing pediatric readmission models. We sought to answer the following research questions. First, how well pediatric readmission prediction model at the time of hospital admission can identify high-risk children compared with at discharge model? Second, Is there any performance tradeoff between the tradeoff between at admission vs at-discharge readmission prediction models? Third, what will be optimal timing for the readmission prediction model and for what type of conditions?

Materials and Methods

Study Setting

Using the Hospital Cost and Utilization Project (HCUP) State inpatient database, this retrospective study included all pediatric admissions from January 1, 2016, to September 30, 2017, across all Florida's hospitals. Developed by the AHRQ, the HCUP SID is an all-payer including the uninsured database of hospital inpatient stays across all non-federal hospitals.[35] The dataset contains patient-level information on demographic characteristics, insurance status, and International Classification of Diseases, 10th Revision, Clinical Modification (ICD-10-CM) diagnosis and procedure codes, patient location, and hospital charges of hospital visits from 265 acute care hospitals across 67 Florida counties. Data on admitting hospital information were obtained from the American Hospital Association (AHA) annual survey. Data on hospitals, including geo-locations, were obtained from the American Hospital Association annual survey. Data on community-level health determinants were derived from the American Community Survey (ACS) by linking patient ZIP codes through Uniform Data System (UDS) Mapper crosswalk.[36] We excluded all adult patients (>18), residential addresses outside Florida, discharges against medical advice (AMA), and cases of in-hospital mortality from the dataset. Institutional review board approval was not required for this study because HCUP does not involve human subjects, and the patients' personal information was de-identified.

Outcome Variable

The primary outcome was all-cause readmission to any Florida hospital within 30 days following discharge of an acute care hospitalization for any unplanned reason. We used the previously validated all-cause Pediatric All-Condition Readmission algorithm by the Boston Children Hospital to identify pediatric readmission.[37] Consistent with the prior studies, only the first readmission within 30 days was considered and subsequent admissions after 30 days from discharge were identified as another index hospitalization.[37,38] Besides, our study considered only readmission events that occur in children younger than 18 years and excluded readmissions for planned procedures and chemotherapy similar to prior studies.[39,40]

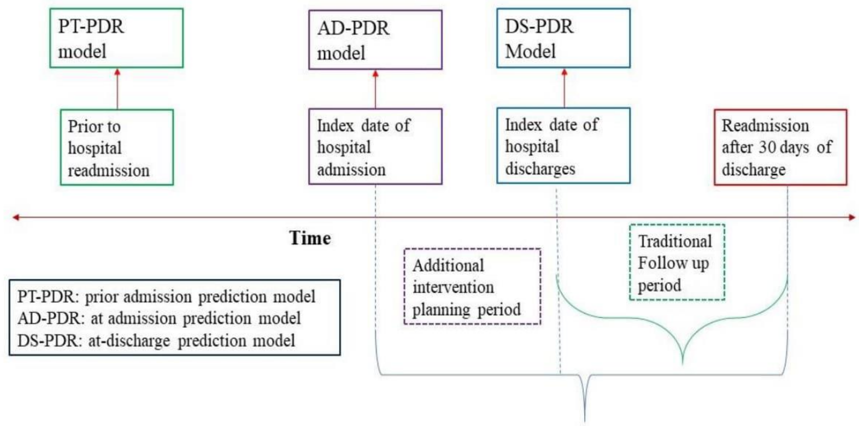

Figure 1: Readmission prediction model at different hospital time points

Predictors

In this study, we evaluated the pediatric readmission prediction model using patient information and available data for two major time points, (1) prediction model that uses data available at the time of hospital admission or transferring to another acute care hospitals, (2) tradition readmission prediction model that uses all available information during discharge time. We also evaluated another hospital admission prediction model to using only available patient information and social determinants of health before any hospitalization event occurs. Predictors for the three models, at admission prediction model (AD-PDR), at-discharge prediction model (DS-PDR), and prior hospital admission prediction model (PT-PDR) were included based on the availability of the information at that certain time point (Figure 1). PT-PDR models included patient demographics, socioeconomic status, provider density, prior hospital visit history, and community-level social determinants of health. At discharge model (AD-PDR) included all variables included in the PT-PDR model, diagnosis presented at the time of hospital admission, and admitting hospitals detailed information. Finally, the traditional at-discharge prediction model (DS-PDR) includes all predictor variables from PT-PDR and AD-PDR models as well as diagnosis, hospital procedures, and discharge information. Table 3.1 shows the predictor variables include all three-readmission prediction models.

Demographic variables included in our study are age (0–1, 1–5, 5-8, 8-12, and ≥ 12), race (African American, White, Hispanic, and others), and gender. Patients' insurance status (public fee for service, Medicaid managed care, private, and uninsured) and community-level social determinants of health were used as proxy measures of patient socioeconomic conditions. History of patient's hospital visits including unplanned treat-and-release emergency department (ED) visits and readmissions within one year of index admissions were also included in our analysis. Provider density was considered as binary variables (high/low), low provider density is considered for if patients live in the designated medically underserved area (MUA) and counties. Designated MUA status was determined using the U.S. Health Resources and Services Administration (HRSA) classification.[41] Social determinants of health (SDH) variables considered in our study were the percentage of people with an income below 100% federal poverty level (FPL), the percentage of homes with no vehicles, the percentage of people with no high school diploma, and the Percentage of the unemployed person. These community-level SDH variables affected hospital visit

behaviors reported in prior studies and included in our study at the ZIP code tabulation area (ZCTA) level, a generalized area representation of the ZIP codes used by the U.S. Census.[42] These predictor variables were used in developing the prior admission risk prediction (PT-PDR) model.

Table 1: Predictor variables for the three pediatric readmission prediction models

Variable Type	Prediction model prior to admission (PT-PDR)	Prediction model at admission (AD-PDR)	Prediction model at Hospital discharge (DS-PDR)
Demographics	X	X	X
Socioeconomic status	X	X	X
Provider density	X	X	X
History of hospital visits	X	X	X
Community-level social determinants of health	X	X	X
Individual-level social determinants of health		X	X
Diagnosis at admission		X	X
Hospital characteristics		X	X
Hospital travel distance		X	X
Diagnosis during hospitalization			X
Hospital procedures			X
Discharge planning			X
Hospital length of stay			X

Hospital-level covariates are children's hospital status, location (division, metropolitan, and micro/rural), ownership status (for-profit and non-profit/government), and hospital bed size (large, medium, and small). Travel distances between patients' residences and discharge hospitals were calculated by geocoding using geographical information software (ArcGIS 10; Ersi Inc., Redlands, CA, USA). The hospital locations were geocoded based on the street addresses and patients' homes into geographic coordinates of home zip code geometric centroids.[43,44] Individual-level SDH variable was a binary variable indicating potential health hazards related to children's family conditions (e.g., housing and parent instability). The ICD-10-CM admitting diagnosis codes used to characterize hospital visits by patient disease complexity for at admission, AD-PDR models. Each of the admitting diagnosis ICD-10-CM codes is included as a binary (yes/no) variable included in the building AD-PDR models. At discharge model (AD-PDR) included all variables discussed above and variables included in the PT-PDR model. Similarly, ICD-10 CM primary diagnosis and procedures codes during hospitalization were coded into individual binary codes and included in the traditional at-discharge model (DS-PDR). The other patient-level factors included only in the DS-PDR model were inpatient LOS (0–3, 3–8, and ≥ 8 days), and discharge planning (routine, post-acute facility, and home health care). The total number of variables included in building the prediction model for PT-PDR, AD-PDR, and DS-PDR was 18, 3721, and 6324, respectively.

Modeling and Analysis

The overall model training and validation process we followed is shown in Figure 2. The overall missing data rate was <0.5%, which we imputed using multiple regression chained equations. We initiated our feature selection process with the variance threshold method, which eliminates features with certain threshold values. We examined the overall distribution of our features and selected a cutoff point of 0.05 for selecting the features. After the variance threshold method, we implemented a chi-square feature selection model with a 0.05 level of significance. The Chi-square feature selection process is computationally efficient and has been widely adopted in prior feature selection research studies.[45] We then used a recursive feature elimination (RFE) technique with a repeated five-fold cross-validation process to evaluate the performance of the prediction model. The RFE approach trained all the available variables and assign a relative weight for the developed prediction model. Therefore, we can eliminate unimportant features by assigning a cutoff weight value. In our case, we set the cutoff value 5% after each iteration, which eliminates 5% of the total number of low weighted features iteratively, until we have the maximum performance metric.

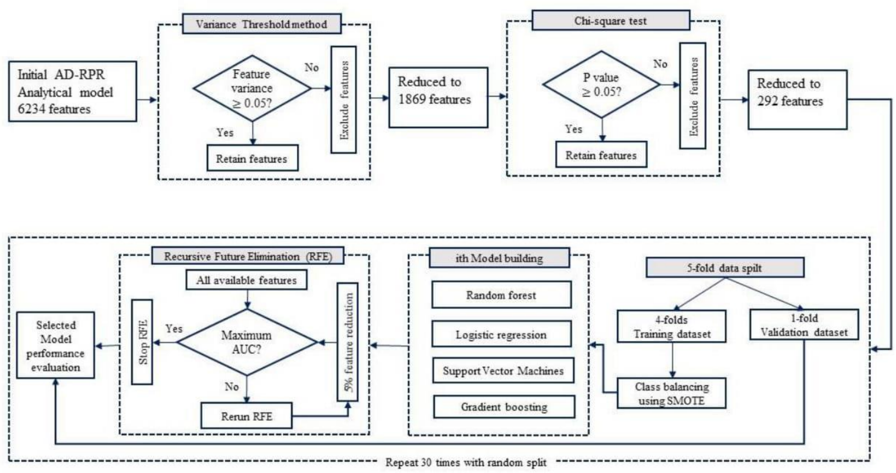

Figure 2: Model building and performance evaluation process

For the repeated cross-validation process, each cohort (e.g., at-discharge AD-PDR) entire dataset was divided into 5 equal cross-validation folds. For each cross-validation repetition, each fold is alternatively used as the test dataset while training our predictors on the other remaining folds. The Hyperparameter of each technique was optimized through a grid search with 10 repeated 5-fold cross-validation iterations. While training, we also explored the issues with class imbalanced problems by using the Synthetic Minority Over-sampling Technique (SMOTE) on the training dataset.[46]. We repeated the cross-validation process 30 times on each cohort to obtain the average performance of each learning model.

We developed and investigated several established tree-based machines-learning algorithms for each model cohort to identify children at high risk for 30-day unplanned readmission. The target variables for the three patient cohorts based on timing was binary variable (yes/no) if the children have been readmitted within 30 days of hospital discharge. To assesses the performance of the learning model, we applied logistic

regression (LR) with backward stepwise selection, Decision tree (C4.5), Support Vector machines (SVM) with the polynomial kernel, Gradient Boosting (GB) algorithms for each disease cohorts. The area under the receiver operating characteristics (ROC) curve (AUC) was used to evaluate the performance of each prediction model. The average AUC values from traditional DS-PDR models were considered as baselines for the performance comparison of the machine-learning algorithms. In addition, we also compared the performance of three all-cause readmission models for those patients who had similar admitting and at-discharge primary diagnoses. All statistical analyses were performed using R studio, and a two-sided p-value less than 0.05 was considered statistically significant.

Results

The analysis included 87865 index hospital visits by 64,597 children (mean [standard deviation] age, 7.8 [5.8]; 32,556 [50.04%] females) from January 1, 2016 to September 30, 2017. Among these index visits, we identified 7288 (8.29%) pediatric hospital visits, those who were readmitted within 30 days. The baseline characteristics for the hospital visits with 30 days readmissions were provided in Table 3.2. The distribution of the timing of 30-days readmission is illustrated in Figure 3.3. We found from our initial analysis that 35.5 % of hospital readmissions occurred within the first seven days of hospital discharge, where the highest percentage of readmission occurred on day 3. Out of the total of 87865 hospital visits, 14849 (16.9%) visits had a different primary diagnosis at discharge time than admitting diagnosis. This dissimilarity between discharge primary diagnosis and admitting diagnosis occurred for the children hospital visits with admitting diagnosis associated with mental health disorder (26.1%), respiratory system disease (7.3%), Injury and poisoning (6.3 %), and Symptoms, signs, and ill-defined conditions (53.2%).

Table 2: Patient and hospital characteristics at 30-day pediatric readmissions

Variable	**Total (N=87865)** **n (%)**	**No Readmission (n = 80577)** **n (%)**	**Readmission (n = 7288)** **n (%)**	**P value**
Age (y)				
0-1	12321 (14.0)	11502 (14.3)	819 (11.2)	<0.001
1-5	14624 (16.6)	13361 (16.6)	1263 (17.3)	
5-8	9020 (10.3)	8344 (10.4)	676 (9.3)	
8-12	11856 (13.5)	10820 (13.4)	1036 (14.2)	
12-17	40044 (45.6)	36550 (45.4)	3494 (47.9)	
Gender				
Male	43882 (49.9)	40141 (49.8)	3741 (51.3)	0.21
Female	43983 (50.1)	40436 (50.2)	3547 (48.7)	
Race				
White	34367 (39.1)	31503 (39.1)	2864 (39.3)	<0.01
African American	26676 (30.4)	24251 (30.1)	2425 (33.3)	
Hispanic/Latin	23079 (26.3)	21341 (26.5)	1738 (23.8)	
Others	3743 (4.3)	3482 (4.3)	261 (3.6)	
Insurance				
Public FFS	10385 (11.8)	9132 (11.3)	1253 (17.2)	<0.01
Medicaid MCO	51928 (59.1)	47830 (59.4)	4098 (56.2)	
Private	20007 (22.8)	18513 (23.0)	1494 (20.5)	

Uninsured	5545 (6.3)	5102 (6.3)	443 (6.1)	
Travel distance (home to index hospital)				
<10 miles	14435 (35.1)	12561 (35.3)	1874 (33.5)	<0.001
10-20 miles	11874 (28.9)	10437 (29.4)	1437 (25.7)	
≥ 20 miles	14798 (34.0)	12524 (35.3)	2274 (40.8)	
Discharge disposition				
Routine	35063 (85.3)	32890 (92.5)	2173 (38.9)	<0.001
Post-acute Facility	4344(10.6)	1003 (2.8)	3341 (59.8)	
Home Health care	1700 (4.1)	1629 (4.7)	71 (1.3)	
Length of stay				
0-3 days	35374 (40.3)	32907 (40.8)	2467 (33.9)	<0.001
3-8 days	24368 (27.7)	22386 (27.8)	1982 (27.2)	
≥ 8 days	28123 (32.0)	25284 (31.4)	2839 (39.0)	
Hospital type				
Children	11513 (13.1)	10203 (12.7)	1310 (18.0)	<0.001
Adult	76352 (86.9)	70374 (87.3)	5978 (82.0)	
Hospital location				
Metro	87447 (99.5)	80167 (99.5)	7280 (99.9)	<0.001
Micro/Rural	418 (0.05)	410 (0.05)	8 (0.01)	
Hospital ownership				
Non-profit /Government	15713 (17.9)	14897 (18.5)	816 (11.2)	<0.001
For profit	72152 (82.1)	65680 (81.5)	6472 (88.5)	
Hospital Size				
Large	56628 (64.4)	51684 (64.1)	4944 (67.8)	<0.001
Medium	26722 (30.4)	24679 (30.6)	2043 (28.0)	
Small	4515 (5.1)	4214 (5.2)	301 (4.1)	

Prediction Performance comparison

Table 3 summarizes the comparative performance of four learning algorithms for three different prediction models. For the prior unplanned admission prediction (PT-PDR) models, the average AUC and 95% confidence interval for the Support Vector Machines with Polynomial Kernel (SVM-P), Logistic regression (LR), Gradient Boosting (GB) and Random Forest (RF) algorithms were 0.57 (0.54-0.60), 0.59 (0.56-0.62), 0.60 (0.57-0.63),0.60 (0.57-0.63) and 0.56 (0.51-0.61), respectively. The average AUC and 95% confidence interval for the SVM-P, LR ,GB and RF models for predicting at discharge readmission (AD-PDR) were 0.68 (0.66-0.70), 0.65 (0.62-0.68), 0.66 (0.64-0.68), 0.61 (0.57-0.65), respectively. Finally , the average performance above mention fours algorithms for the traditional at-discharge prediction model (DS-PDR) were 0.73 (0.70-0.76), 0.69 (0.66-0.72), 0.67 (0.63-0.71) and 0.64 (0.60-0.68), respectively. Among all four algorithms, RF models showed the lowest average AUC for all three prediction models. SVM with Polynomial Kernel algorithms outperformed all other algorithms for AD-PDR and DS-PDR models, while in PT-PDR the Gradient Boosting model outperforms other algorithms. The performance of the at-admission (AD-PDR) model was comparable with the at-discharge (DS-PDR) model for all four algorithms.

After excluding hospital visits with admitting diagnosis for symptoms, signs, and ill-defined conditions, and mental health disorder, we also developed a revised at-admission (AD-PDR) model and compared it with the at-discharge (DS-PDR) prediction models using above mentioned four algorithms. Table 3.4 summarizes the comparative performance of four learning algorithms for three revised prediction models. The performance of the best at-admission (AD-PDR) model was practically comparable with the at-

discharge (DS-PDR) model (Table-4). The performance of the revised AD-PDR models was improved for all learning algorithms. For the PT-PDR models, the average AUC and 95% confidence interval remained similar to the prior results reported in Table 3.3. Like prior original models, SVM with Polynomial Kernel algorithms outperformed all other algorithms for revised AD-PDR and DS-PDR models. The average AUC and 95% confidence interval for the SVM-P, LR ,GB and RF models for revised AD-PDR were 0.70 (0.68-0.72), 0.67 (0.65-0.69), 0.66 (0.64-0.68), 0.62 (0.59-0.65), respectively. Finally , the average performance above mention fours algorithms for the traditional at-discharge prediction model (revised DS-PDR) were 0.71 (0.68-0.72), 0.67 (0.65-0.69), 0.64 (0.60-0.68) and 0.64 (0.60-0.68), respectively. Among all four algorithms, RF models showed the lowest average AUC for all three prediction models.

Table 3: AUC Performance comparison of the Predictive Models

Machine learning Algorithms	Prediction before admission (PT-PDR) (AUC, 95% CI)	Prediction at admission (AD-PDR) (AUC, 95% CI)	Prediction at discharge (DS-PDR) (AUC, 95% CI)
Support Vector Machines with Polynomial Kernel	0.57 (0.54-0.60)	**0.68 (0.66-0.70)**	**0.73 (0.70-0.76)**
Logistic regression	0.59 (0.56-0.62)	0.65 (0.62-0.68)	0.69 (0.66-0.72)
Gradient Boosting	**0.60 (0.57-0.63)**	0.66 (0.64-0.68)	0.67 (0.63-0.71)
Random Forest	0.56 (0.51-0.61)	0.61 (0.57-0.65)	0.64 (0.60-0.68)

Important features of pediatric readmissions

We also extracted important features from the Random Forest algorithms for all three prediction models. The top 10 important features are shown in Table 3.5. Important features associated with increased readmission risk varied widely across the type of prediction model and were mostly related to patients' demographics, SDHs, clinical factors, and hospital characteristics. The history of the prior hospital visits was most important for the PT-PDR model and second most important features for both AD-PDR and DS-PDR models. The higher the accumulated times a child has been visited the hospital, the more likely the patient will be readmitted after hospital discharge. The low healthcare provider density was found an important factor for the three readmission prediction model. Discharges to post-acute facilities and longer travel distances were also found within the top ten important features for both the at-admission and at-discharge models. Children's insurance status with Public Managed Care was found within the top five most weighted features for PT-PDR and AD-PDR models. African American children, children aged 5 to 8, and adolescent children were significantly associated with increased readmission risk for only for PT-PDR models.

The presence of comorbidity and complex procedures were also important predictors of readmission for AD-PDR and DS-PDR. Disruptive mood disorder was the most important feature for both AD-PDR and DS-PDR models. The other important clinical features for the AD-PDR model were Dehydration and Abdominal pain. For the DS-PDR model, Pneumonia and Major Depressive Disorder- recurrent were other top ten clinical diagnoses related to high-risk readmission. The Drainage of the Spinal Canal and Resection

of the Appendix procedure was also found important for predicting readmission at the DS-PDR model. Children's hospital status was only found important for the AD-PDR model and longer hospital stay was found within the top ten features for DS-PDR models. Children living with challenging family conditions and in poor neighborhoods were found as important features for both PT-PDR and AD-PDR models. Similarly, children living in communities with fewer high school diplomas and a higher percentage of unemployed persons were found important for the PT-PDR models.

Table 4. Important features extracted by Support Vector Machines with Polynomial algorithm

Rank	Features in PT-PDR model (weight)	Features in AD-PDR model (weight)	Features in DS-PDR model (weight)
1	Prior hospital visit (0.31)	Disruptive mood disorder (0.24)	Disruptive mood disorder (0.16)
2	Age (12-17) (0.09)	Prior hospital visit (0.11)	Prior hospital visit (0.10)
3	Provider density (0.08)	Dehydration (0.09)	Pneumonia (0.08)
4	Public Managed Care (0.06)	Abdominal pain (0.06)	Major Depressive Disorder- recurrent (0.08)
5	African American (0.05)	Public Managed Care (0.05)	Drainage of Spinal Canal (0.06)
6	% of people with an income below 100 FPL (0.4)	Provider density (0.05)	Length of stay (0.05)
7	% of people with no high school diploma (0.04)	Post-acute facility (0.05)	Resection of Appendix (0.03)
8	Age (5-8) (0.04)	Hospital travel distance (0.02)	Post-acute facility (0.03)
9	% of the unemployed person (0.03)	% of people with an income below 100 federal poverty level (0.02)	Provider density (0.03)
10	% of homes with no vehicles (0.02)	Children Hospital (0.02)	Hospital travel distance (0.02)

Discussions

In summary, we developed and compared several variants of machine-learning-based predictive models for three different hospital admission timepoints that can improve the prediction of pediatric readmission, with the possibility of early pediatric readmission risk prediction. To our knowledge, this is the first study to develop an at-admission pediatric readmission model and compared prediction performance with the traditional at-discharge readmission prediction model. Our proposed at-admission all-causes readmission prediction model showed comparable prediction performance compared with the at-discharge model. In addition, our proposed revised AD-PDR models excluding two-body system diagnosis showed improved and almost similar prediction performance compared with the DS-PDR model. In terms of predictive

power, the models we developed showed comparable results with other published works.[27,28,30,47,48] However, these models considered all-condition or all-surgeries 30-days readmission during hospital discharge time point, therefore lacks the ability to an equivalent comparison of these models to our proposed DS-PDR models. Therefore, this study highlights the potential of the AD-PDR model in identifying high-risk children during hospital admission over traditional at-discharge approaches.

The similar performance of the AD-PDR models and DS-PDR models reported in this study suggest that pediatric readmission risk prediction during both at-discharge and at- hospital admission can be used by hospital providers to design and implement appropriate intervention programs. This additional time provided by the early readmission risk prediction (AD-PDR) model could allow comprehensive care transition and discharge planning particularly for high risk returning patients.[49,50] Although, AD-PDR model allows early pediatric readmission prediction, the model potentially misclassify certain patient population, mainly due to lack of adequate diagnosis data. This misclassification of the initial AD-PDR model is likely related to the patients admitted for unclear admitting diagnosis (e.g., unspecified fever and abdominal pain), since their primary diagnosis usually (53.2% reported in our study) changed after additional clinical tests. Besides, predicting readmission for children with unspecified mental health disorders is challenging due to the unpredictable nature of the episodes.[51] Consequently, our revised AD-PDR model excluding patient population with unclear admitting diagnosis and mental health disorder, showed improved prediction performance.

In our study, we found a variation of extracted important features across three readmission prediction models. History of prior hospital admissions, medical complexity, and non-acute post-discharge was found important features in predicting readmission, which is consistent with the previous investigations.[25,27,31,52]Although these factors are not easily modifiable for most conditions, comprehensive intervention strategies including better discharge planning (e.g., telephone call) and care coordination can mitigate the risk of pediatric readmission.[15,53–55] The findings of prior hospital visits in all three readmission models suggest that there might exist an unresolved system issue associated with the quality and clarity of discharge education and access to pediatric care for a certain patient population.[39] Besides, living in medically underserved communities as important significant factors suggests residents in these areas may have limited access to pediatric care due to geographical location.[56,57] This unequal access to care might result from a combined effect with persistent rural-urban disparities in pediatric are access and a high degree of pediatric care regionalization.[57–59] These findings highlight the policymakers the need to develop a tailored interventions/programs particularly, for these MAU areas ensuring necessary pediatric care access. Besides, several important community-level SDHs features (e.g., high school graduation and employment rate) found in our study in readmission prediction suggest in pediatric care due to socioeconomic inequality.[60,61] Moreover, longer travel distance as important factors suggests the persistence of rural-urban disparities in children's healthcare due to high regionalization of pediatric care.[71] Therefore, interventions including components that are implemented before (e.g., parent education and health literacy) and after discharge (e.g., need-based assistance programs and discharge follow-up appointments) can help to mitigate readmission risk across the vulnerable population.[62]

Limitations and Future directions

This study has several common limitations, most of which are related to a retrospective analysis of administrative claim databases. First, the HCUP database is an administrative claim dataset that uses ICD codes to classify patients' medical diagnoses, procedures, and outcomes. The possibility of coding inaccuracy or incorrect information cannot be dismissed. Second, although our study makes a significant contribution of presenting an at-admission readmission prediction model across Florida hospitals, the findings of this study may not be generalizable to other U.S. state or international countries' patient

populations. Third, our research did not include information regarding laboratory tests, patient detailed vitals, parent health literacy, and post-acute care quality, thus, including these factors may have improved prediction performance. Fourth, the dataset does not include data from federal hospitals or out-of-hospital deaths or readmissions after the initial index admission. However, pediatric admissions in federal hospitals few in relation to non-federal hospitals and out of state pediatric readmissions are expected to have minimal impact on our results, due to the unique geographical location of Florida State. Finally, we include community-level SDHs in the ZTCAs level, and more precise census tract level data or patient-provided information may have improved accuracy in capturing community-level variables.

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Appendix E: Identifying Children at Readmission Risk: Cohort-Specific Versus All-Cause Readmission Prediction Readmission Prediction

Appendix E shows the manuscript titled, " Identifying Children at Readmission Risk: Cohort-specific versus all-cause readmission prediction readmission prediction ", which is under review in *Machine Learning with Applications* Journal.

Identifying Children at Readmission Risk: Cohort-specific versus all-cause readmission prediction model

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Abstract

Backgrounds: Although pediatric readmissions are costly and potentially preventable, accurately predicting and reducing readmission risk in children remains challenging. Machine learning has the potential to improve predictive power by identifying complex-nonlinear relationships within datasets. Our objective was to assess whether machine learning can better identify readmission risk in children hospitalized for common pediatric conditions.

Methods: Using the Hospital Cost and Utilization Project database, this prognostic study included pediatric hospital discharges access non-federal hospitals in Florida from January 2016 through September 2017. Five machine-learning algorithms (random forest, naïve Bayes, support vector machines, adapting boosting, neural networks) were compared with the traditional approach (logistic regression and all-cause readmission) to predict 30-day unplanned readmission for two acute (appendicitis and pneumonia) and three chronic (asthma, seizure, and sickle cell) conditions. The model's performance was measured by the area under the curve (AUC). Risk factors were identified using multivariate regression techniques.

Results: The performance of the best model varied widely depending on the index diagnosis, with average AUC ranges from 0.60 for appendicitis to 0.71 for pneumonia. Compared with the logistic regression, machine-learning algorithms showed considerable improvement in AUC for asthma, seizure, and pneumonia. Depending on the admission causes, factors such as higher comorbidity score, readmissions history, post-acute discharge, race, and certain social determinants of health factors were associated with increased risk of readmissions.

Conclusions: Condition-specific machine-learning methods improved the readmission prediction in most pediatric conditions. Significant risk factors varied widely by index diagnosis, indicating disease-specific multifaceted intervention plans may help to reduce adverse pediatric outcomes.

Introduction

Hospital readmissions disrupt the daily lives of patients and families, expose patients to the risk of hospital-acquired conditions and other nosocomial harm including stress and negative developmental effects (Calfee, 2012; Jencks et al., 2009; Schuster et al., 2011). Preventable readmissions have not only been linked to the provider quality of care, but they also pose a significant financial burden to the US healthcare system (Vest et al., 2010; Walraven et al., 2011). In 2014 national estimates by the Agency of Healthcare Quality (AHRQ), readmissions within 30-days resulted in hospital cost of $2.1 billion for children and $50.4 billion for adults (*HCUPnet, Healthcare Cost and Utilization Project. Agency for Healthcare Research and Quality. Rockville, MD, USA*, 2014). Hence, reducing these unplanned events has become a focus for quality-improvement efforts and major health policy concerns (Kripalani et al., 2014; Nakamura et al., 2014). For older patients, the Centers for Medicare and Medicaid Services (CMS) implemented the Hospital Readmission Reduction program nationwide in 2012 that penalize hospitals with excess Medicare readmissions for the targeted conditions (McIlvennan et al., 2015). Similarly, many states have begun decreasing payments to hospitals and Managed Care Organizations (MCO) with excess Medicaid readmissions (Commission, n.d.; Massachusetts Executive Office of Health and Human Services, n.d.). These efforts resulted in a significant reduction in readmissions, particularly for targeted adult populations (8% nationally between 2010 and 2015) (Hasan et al., 2020). However, pediatric readmission rates have increased by 8.2% nationally between 2010 and 2016 (Bucholz et al., 2019).

With the wide adoption of electronic medical record systems, ways to prevent hospital readmissions have focused on predictive analytics to identify patients at greater risk of being readmitted (Kash et al., 2017; Kripalani et al., 2014; Triantafillou, 2017). Readmission prediction models potentially enable direct general or disease-specific interventions toward those who might need most by identifying high-risk patients (Artetxe et al., 2018). Readmissions of adult patients have been the subject of substantial research and tackled by diverse predictive approaches (Mahmoudi et al., 2020; Wan et al., 2016). However, readmission predictions for children have received limited attention (Berry et al., 2011; Feudtner et al., 2009). Most studies in pediatric readmission are thus far limited to the examination of patient populations susceptible to readmission and the variability of readmission rates across hospitals (Berry et al., 2013; Zhou et al., 2019). Few studies reported predictive models using both the adult and pediatric populations (Garmendia et al., 2017). However, these models resulted in lower sensitivity for pediatric patients due to a greater class imbalance in the pediatric population. More recently, researchers showed promise in predicting all-condition of pediatric readmissions using traditional learning algorithms (Ehwerhemuepha et al., 2020; Taylor et al., 2020; Wolff et al., 2019). However, no studies have developed and compared the machine-learning based readmission prediction models for specific index conditions. Studies showed that readmission prediction performance can be improved by building predictive models using a stratified patient population (Besga et al., 2015; Burke et al., 2017). Moreover, no studies have examined how the factors including social determinants influence the risk of readmission for different index conditions.

The rates of pediatric readmissions vary greatly (~3%-30%) depending on the index diagnosis and diagnosis for the most readmissions were similar to the diagnosis as the index hospitalization, suggesting the need for condition-specific interventions (Bardach et al., 2013; Berry et al., 2013). Therefore, strategies for reducing readmissions need to account for the index diagnosis to better target the high-risk patients and risk-factor for readmission (Bucholz et al., 2018). In addition, understanding how the risk factors of readmission vary by index condition may provide insight into general versus disease-specific interventions (Auger et al., 2014; Coller et al., 2014). Identifying the children at high readmission risk is critical to better target readmission reduction interventions by improving discharge planning, parent-provider care coordination, and ultimately improve quality of care (Auger et al., 2014). Subsequently, this study constructed and compared predictive models based on supervised machine learning algorithms to identify children with the risk of 30-day readmission for two acute and three chronic conditions. These index conditions were selected for the high prevalence of hospital admission and/or readmission as well as the preventability of the 30-day readmissions (Berry et al., 2013; Gay et al., 2015). In addition, we identified and compared significant readmission risk factors across different index conditions to better understand the opportunities to design future targeted interventions.

Methods

Data

Using the Hospital Cost and Utilization Project (HCUP) State inpatient database, this retrospective study included all pediatric admissions from January 1, 2016, to September 30, 2017, across all Florida's hospitals. Developed by the AHRQ, the HCUP SID is an all-payer including the uninsured database of hospital inpatient stays across all non-federal hospitals (*HCUP State Inpatient Databases (SID). Healthcare Cost and Utilization Project (HCUP). 2016-2017.*, n.d.). Data on admitting hospital information were obtained from the American Hospital Association (AHA) annual survey. Data on community-level health determinants were derived from the American Community Survey (ACS) by linking patient ZIP codes through Uniform Data System (UDS) Mapper crosswalk (*Uniform Data System (UDS) Mapper.*, n.d.).

Study Population

The disease cohorts included in the study are two acute conditions (appendicitis and pneumonia) and three chronic conditions (asthma, seizure, and sickle cell disease). We excluded adult patients (>17 years), residential addresses outside the state of Florida, against medical advice (AMA) discharges, discharged to another acute care setting, and in-hospital mortality from the dataset. The disease cohorts were identified using the International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) codes. Appendicitis index admission was identified as the principal diagnosis of appendicitis and procedure code for an appendectomy. Sickle cell disease (SCD) was defined as a principal diagnosis of sickle cell disorder excluding sickle cell trait diagnosis. ICD-10-CM discharge diagnosis codes for the disease cohorts are shown in Appendix Table 1. IRB approval was not required for this study because the patients' information was de-identified in the HCUP SID database.

Outcome Measures

The primary outcome was readmission within 30 days following discharge of an index hospitalization for five index conditions. Condition-specific pediatric readmission is defined as the inpatient hospitalization for any unplanned cause occurring within 30 days of index condition-specific admission discharges. Consistent with the Pediatric All-Condition Readmission Measure by the Boston Children Hospital, only the first readmission within 30 days was considered and subsequent admissions after 30 days from discharge were identified as another index hospitalization (*Boston Children's Hospital. Readmissions.*, n.d.; *National Quality Forum. Pediatric All-Condition Readmission Measure.*, n.d.). Besides, we excluded readmissions for planned procedures and chemotherapy.

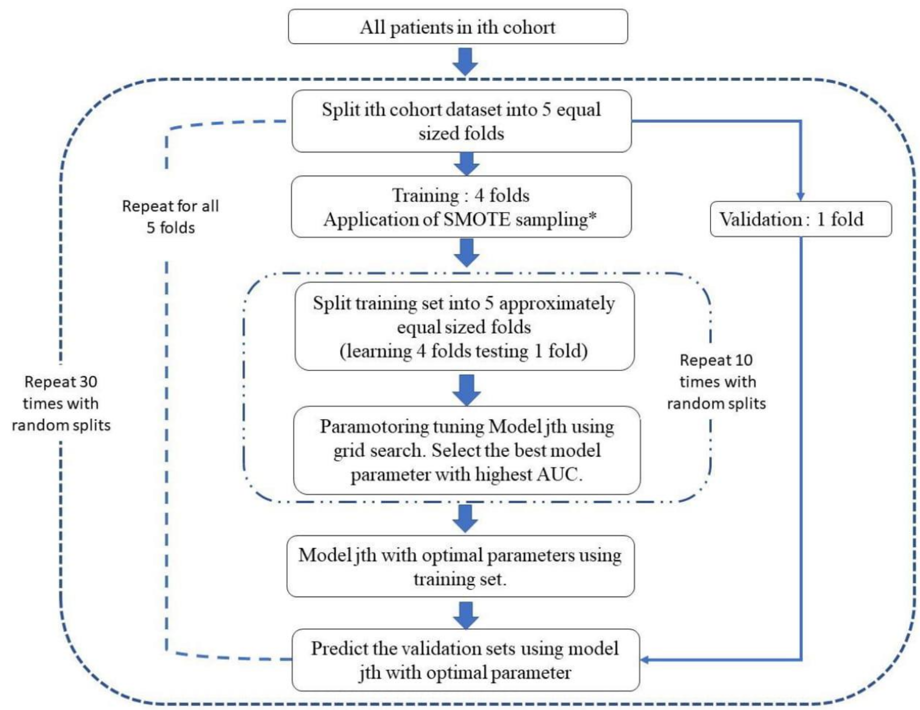
Predictors

The candidate variables for our model included demographics, socioeconomic status, clinical aspects, hospital travel distances, medical history, and social determinants of health (SDH) factors. Demographic variables included in our study are age, race, and gender. The other patient factors included are payer information, inpatient length of stay, and discharge planning. Hospital level covariates are children's hospital status, hospital location, ownership status. For the patient comorbidities, 27 common pediatric pathologies were evaluated and then weighted summed to generate a pediatric comorbidity score (Tai et al., 2006). History of patient's hospital visits including unplanned treat-and-release emergency department (ED) visits and readmissions within one year of index admissions were also included in our analysis. Travel distances between the patient's residence and the discharged hospital were calculated using geographical information software (Cloyd et al., 2017; Mohr et al., 2016). The individual-level SDH variable was a binary variable indicating potential health hazards related to children's family conditions (e.g., housing and parent instability). Community-level SDH variables were poverty level (percentage of people living below 100% federal poverty level), education (the percentage of people with no high school diploma), and employment (the Percentage of the unemployed person) data available at the ZIP code tabulation area (ZCTA) level (*State Population Totals and Components of Change: 2010-2019*, n.d.).

Modeling and Analysis

The overall model training and validation process we followed is shown in Figure 1. The overall missing data rate was <0.5%, which we imputed using multiple stochastic chained equations (Li et al., 2015). Multicollinearity between candidate variables was also assessed using the variance inflation factor analysis (Thompson et al., 2017). We used a repeated five-fold cross-validation process to evaluate the performance of the prediction model. First, each disease cohort's entire dataset was divided into 5 equal cross-validation folds for the repeated cross-validation process. For each cross-validation repetition, each fold is alternatively used as the test dataset while training our predictors on the other remaining folds. Hyperparameter tuning for each fold was also conducted during model training to further optimize the model performance. The Hyperparameter of each technique was optimized through a grid search with 10 repeated 5-fold cross-validation iterations. While training, we also explored the issues with class imbalanced problems by using the Synthetic Minority Over-sampling Technique (SMOTE) on the training dataset (Chawla et al., 2002). We repeated the cross-validation process 50 times on each cohort dataset to obtain the average performance of each learning model.

Figure 1: Model building and performance evaluation process. * Models were built with and without SMOTE



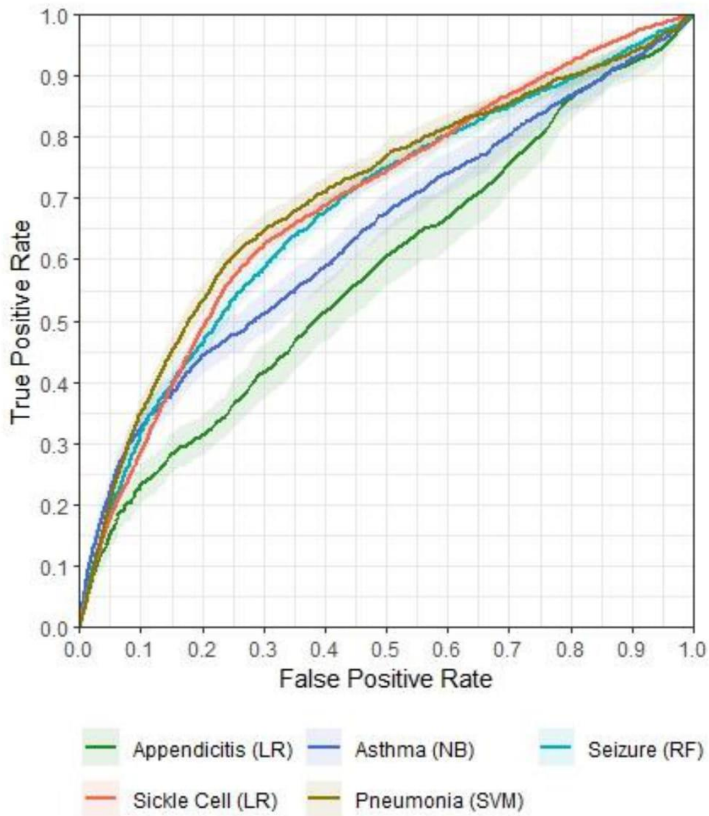
Predictive models were developed using both classical and ensemble machine-learning algorithms for each disease cohort. For traditional methods, we applied logistic regression (LR) with backward stepwise selection, Naïve Bayes (NB), Support Vector machines (SVM) with the polynomial kernel, feed-forward Multilayer Perceptron neural network (MPNN) algorithms. For the ensemble methods, we used Adapting Boosting (AdaBoost) and Random Forest (RF) algorithms for readmission modeling. Details of model development and

hyperparameters are available in Appendix Table 2. The area under the receiver operating characteristics (ROC) curve (AUC) was used to evaluate the performance of each prediction model. The average AUC values from classical LR models were considered as baselines for the performance comparison of the machine-learning algorithms. Furthermore, we also compared the performance of the best all-cause readmission model with the condition-specific best model in predicting readmission for five index diagnoses.

Results:

The analysis included 88,547 index hospital visits by 64,597 children (mean [standard deviation] age, 7.8 [5.8]; 32,556 [50.04%] females) from January 1, 2016 to September 30, 2017. Among these index visits, we included 1751, 4623, 2026, 2692, and 2721 index admissions for appendicitis, asthma, seizure, SCD, and pneumonia cohorts based on inclusion criteria. The baseline characteristics of the disease cohorts are provided in Table 1. Rates of 30-day readmission were 3.3% for appendicitis, 2.9% for asthma, 8.7 % for seizure, 20.5% for SCD, and 6.8% for pneumonia. The median hospital readmission charge was $21640 with an interquartile range ($13847-$38213), and total readmissions-related hospital charges were $81.7 million for these five conditions.

Figure 2: Average ROCs of the best performing machine learning approaches for the disease cohorts. The solid line corresponds to the ROC mean. (LR – Logistic Regression, NB- Naïve Bayes, RF- Random forest, SVM- Support Vector Machines with the polynomial kernel)



Assessment of the prediction models

Table 2 summarizes the performance of the learning algorithms with and without SMOTE balancing by index conditions. Compared with the classical LR, machine-learning algorithms showed improvement for asthma, seizure, and pneumonia. Nevertheless, LR models ranked within the top three in all cohorts and outperformed other algorithms for appendicitis and SCD. SVM models outperformed LR for asthma and pneumonia, whereas for pneumonia SVM models outperformed any other algorithms. RF models outperformed for the seizure, whereas NB models achieved a higher average AUC compared with other algorithms for asthma. Conversely, the AdaBoost and MPNN models did not rank the top three for any disease cohorts. Figure 2 shows the average ROC curves for the best performing algorithms by disease cohorts. The average AUC metric for best performing models varied widely across the disease cohort, ranging lowest from 0.60 for appendicitis to the highest 0.71 for pneumonia. The introduction of SMOTE with learning algorithms showed mixed improvement in model performance. For SCD and pneumonia, SMOTE with LR and SVM achieved the highest AUC across all models. SMOTE yielded the highest improvement (~19.31%-23.13%) in AUC for the SVM models. Besides, SMOTE with SVM algorithms achieved the highest AUC of 0.68 for all-cause 30-day readmission models. However, the best all-cause model showed lower predictive performance compared with the best cohort-specific readmission models except for appendicitis (Appendix Table 3).

Predictors of pediatric readmissions

Results from regression analyses by disease cohorts are shown in Table 3 and Appendix Table 4. Factors associated with increased readmission risk varied widely across cohorts and were mostly related to patients' demographics, SDHs, clinical factors, and hospital characteristics. The history of the readmissions was statistically significant across all disease groups, except for appendicitis. The higher the accumulated times a child has been readmitted to the hospital, the more likely the patient will be readmitted after hospital discharge. Discharges to post-acute facilities have higher odds of being readmitted than routine discharge in patients with seizure, SCD, and pneumonia. The presence of higher comorbidity scores were also predictors of readmission except for appendicitis. Length of stay was identified as significant for seizure and SCD. The longer patient has stayed in the hospitals, the higher the likelihood of being readmitted within 30 days of index discharge. Moreover, children who were initially admitted to children's hospitals with appendicitis and pneumonia were less likely to be readmitted compared with adult hospitals.

African American children, longer hospital travel distance, and small hospital bed size were significantly associated with increased readmission risk for SCD. Besides, Hispanic raced children after appendicitis and seizure discharge were more likely to be readmitted compared to a white children. SDH factors were also found significant in children with asthma, SCD, and pneumonia. Children living with challenging family conditions and in poor neighborhoods were associated with an increased risk of readmission for SCD. Similarly, children living in communities with fewer high school diplomas and a higher percentage of unemployed persons were more likely to be readmitted for pneumonia and asthma, respectively. Gender was only found significant in asthma cohorts, with a higher likelihood of readmission for female patients. However, the patient's insurance type, previous ED visits, and hospital ownership type were found statistically insignificant for any cohorts.

Discussion:

In summary, we developed and compared several variants of machine-learning predictive models that can improve the prediction of pediatric readmission for specific acute and chronic diseases. To our knowledge, this is the first study to apply and compare machine-learning algorithms to predict pediatric readmission across common multiple index conditions. In terms of predictive power, the models we developed showed comparable results with other published works depending on the disease cohorts (Garmendia et al., 2017; Polites et al., 2017; Taylor et al., 2020; Wolff et al., 2019; Zhou et al., 2019). However, the majority of these models consider either all-condition or all-surgeries 30-days readmission and did not report the model's performance on the different index conditions, these factors hinder an equivalent comparison of these models to our proposed models. The all-cause model in our study showed lower discrimination compared with cohort-specific readmission models and suggests a single all-cause model for readmissions prediction in the clinical

setting may be insufficient (C. G. Walsh et al., 2017; C. Walsh & Hripcsak, 2014). Machine-learning models developed in our study improved the readmission prediction for the majority of pediatric conditions compared with traditional LR similar to prior studies (Morgan et al., 2019; Mortazavi et al., 2016; Weng et al., 2017). The introduction of SMOTE with machine learning also showed a considerable improvement in AUC consistent with previous outcomes prediction studies using an unbalanced dataset (Cui et al., 2018; Symum & Zayas-Castro, 2020b; Wolff et al., 2019). Taken together, this study reinforces the potential role for the integration of advanced machine-learning models over traditional approaches into clinical practice for identifying high-risk populations after initial hospitalization (Awan et al., 2019; Zack et al., 2019).

In the study, we found a significant association of history of readmission, higher comorbidity scores, and non-acute post-discharge with increased risk of readmission, which is consistent with previous investigations (Beck et al., 2006; Bucholz et al., 2018; Feudtner et al., 2009; Zhou et al., 2019). Although these factors are not easily modifiable for most conditions, passive intervention strategies targeting these high-risk patients such as better parent-provider coordination and improving family social health needs can mitigate the risk of pediatric readmission (Auger et al., 2014; Ehwerhemuepha et al., 2018; Emechebe et al., 2019; Kripalani et al., 2014). The increased likelihood of a history of previous readmissions and following readmission suggests that there might exist an unresolved systematic issue associated with the quality and clarity of discharge education and parent instruction for a certain patient population (Ehwerhemuepha et al., 2018). On the other hand, the association between post-acute care discharge and readmission may indicate the prevalence of care transition complications resulting from fragmented care (Berry et al., 2011; Britton et al., 2017). Children with complex chronic conditions often require a heightened complexity of discharge care planning between an array of community and hospital-based providers (Lye et al., 2010; Srivastava et al., 2005). High-quality discharge planning including timely communication and post-discharge instruction with outpatients' providers and home healthcare may reduce the risk of frequent readmissions (Berry et al., 2011; Kripalani et al., 2007).

Reducing disparities in pediatric care may also help mitigate the risk of readmissions. We found increased readmission risk associated with African American and Hispanic children similar to prior studies (Berry et al., 2011, 2013; Feudtner et al., 2010). Children with these attributes are less likely to have access to primary care or other health care provider that could help to maintain children's health after hospital discharge (Flores, 2010; Flores, Olson, et al., 2005). The language barrier may contribute to poorer healthcare access and adverse health outcomes for Hispanic/ Latino children particularly those living in households with limited English proficiency (Flores, Abreu, et al., 2005; Flores & Lin, 2013). The significant association between community-level SDHs (e.g., high school graduation and employment rate) and increased risk of readmissions suggests disparities in pediatric care due to socioeconomic inequality (Sills et al., 2016; Sokol et al., 2019). Moreover, the increased likelihood of readmission with longer travel distance suggests the persistence of rural-urban disparities in children's healthcare due to the high regionalization of pediatric care (França & McManus, 2018; Lorch et al., 2009; Symum & Zayas-Castro, 2020a). Unequal access to health services and quality care is likely to impact children's overall well-being and mental health, consequently, increase the occurrence of unwanted health outcomes. Interventions addressing social health determinants and disparities in pediatric care such as need-based assistance programs, promoting health literacy, early childhood screening, and community-based care can help to mitigate readmission risk and, thus contribute to reducing unwanted healthcare expenditures (Cheng et al., 2015; Coller et al., 2014; Emechebe et al., 2019; Healy-Collier et al., 2016).

Our study has several limitations, most of which are related to the HCUP state inpatient administrative data. First, the predictions were made using selected retrospective patient populations within a single U.S. state, generalizations to other states or clinical settings may not be applicable. Second, diagnosis and procedures in the HCUP databases are recorded in ICD codes, some inaccuracy in the coding cannot be excluded. Besides, there might be also some disparity in SDH ICD codes to capture individual-level SDHs (Torres et al., 2017). Third, due to the statewide limitation of the HCUP SID database, we were unable to identify out-of-hospital deaths or readmissions to hospitals out-of-state from the initial index admission. Fourth, our research did not include information regarding the parent health literacy, and post-acute care quality, thus, including these factors may have marginally improved prediction performance. Finally, we include community-level SDHs in the

ZTCAs level, and more precise census tract level data may have improved accuracy in capturing community-level variables.

Conclusions

Depending on the index admission diagnosis, a considerable proportion (~2.9%-20.5%) of children who are discharged from hospitals readmitted within 30 days. These unplanned events burden the pediatric health system financially and may potentially hinder the child's normal growth. More efficiently targeting children at higher risk of readmission through advanced predictive models may be the first step toward implementing preventive treatment programs. Condition-specific machine-learning methods we developed showed a considerable improvement in readmission prediction over traditional LR and all-cause readmission models, substantiates the promising prospect of machine-learning in clinical settings with the ability to leverage all available data and their complex relationships. Besides, improved condition-specific machine-learning models may assist the drive towards more efficient and cost-effective readmission interventions, by increasing the number of potential children who might benefit, while avoiding unnecessary treatment of others. Consequently, the intriguing variation we found in the readmission risk factors by the admission causes also supports the need to consider disease-specific risk assessment and implement associated intervention programs. Since both clinical and non-clinical factors likely to play role in increased readmission risk, we recommend multifaceted and targeted interventions including family assistance programs, parental health literacy, strong discharge planning including regular follow-up and community-based care.

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Table 1: Descriptive statistics of all pediatric discharges, including readmitted and no readmitted patients by reason for admission

Variable	Appendicitis (N=1751)	Asthma (N=4623)	Seizure (N=2026)	Sickle Cell (N=2692)	Pneumonia (N=2721)
Readmitted, n (%)					
No	1693 (96.7)	4486 (97.1)	1849 (91.3)	2141 (79.5)	2537 (93.2)
Yes	58 (3.3)	137 (2.9)	177 (8.7)	551 (20.5)	184 (6.8)
Age (y), n (%)					
0-5	84 (4.8)	1546 (33.4)	743 (36.7)	284 (10.5)	1471 (54.1)
5-8	205 (11.7)	1154 (24.9)	320 (15.8)	306 (11.4)	531 (19.5)
8-12	511 (29.18)	1135 (24.6)	345 (17.3)	598 (22.2)	378 (13.9)
12-17	951 (54.31)	788 (17.0)	618 (30.5)	1504 (55.8)	341 (12.5)
Gender, n (%)					
Male	1098 (62.7)	2826 (61.1)	1151 (56.8)	1268 (47.1)	1466 (53.9)
Female	653 (37.3)	1797 (38.9)	875 (43.2)	1424 (52.9)	1255 (46.1)
Race, n (%)					
White	725 (41.0)	967 (20.9)	782 (38.6)	36 (1.3)	810 (29.8)
African American	234 (13.4)	2473 (53.5)	655 (32.4)	2476 (91.9)	919 (33.7)
Hispanic/Latin	731 (41.7)	1013 (21.9)	497 (24.5)	135 (5.0)	860 (31.6)
Others	61 (3.5)	170 (3.6)	92 (4.5)	45 (1.7)	132 (4.8)
Travel distance (home to hospital), n (%)					
<20 miles	1282 (73.2)	3954 (85.5)	1336 (66.0)	2184 (81.1)	2133 (78.4)
≥ 20 miles	469 (26.8)	669 (14.5)	690 (34.0)	508 (18.9)	588 (21.6)
Disposition, n (%)					
Routine	1732 (99.0)	4517 (98.0)	1966 (97.0)	2656 (98.7)	2653 (97.5)
Post-acute care	19 (1.0)	106 (2.0)	60 (3.0)	36 (1.3)	68 (2.5)
Length of Stay, n (%)					
0-3 days	1280 (73.1)	4081 (88.3)	1690 (83.4)	1563 (58.1)	1977 (72.7)
3-8 days	358 (20.4)	479 (10.4)	251 (12.4)	857 (31.8)	555 (20.4)
≥ 8 days	113 (6.4)	63 (1.4)	85 (4.2)	272 (10.1)	189 (6.9)
Insurance					
Public FFS	133 (7.5)	410 (8.9)	284 (14.0)	625 (23.2)	303 (11.1)
Medicaid MCO	1032 (58.9)	3368 (72.9)	1115 (55.0)	1517 (56.3)	1846 (67.8)
Private	470 (26.8)	627 (13.6)	471 (23.23)	348 (12.9)	425 (15.6)
Uninsured	116 (6.62)	218 (4.7)	156 (7.7)	202 (7.5)	147 (5.4)
Previous unplanned readmission					
0	1699 (97.0)	4084 (88.3)	1505 (74.3)	910 (33.8)	2180 (80.1)
1-2	35 (2.0)	326 (7.0)	239 (11.8)	436 (16.2)	247 (9.1)
≥ 3	17 (1.0)	213 (4.6)	282 (13.9)	1346 (50.0)	294 (10.8)
Previous unplanned ED visits					
0	793 (45.3)	1237 (26.7)	835 (41.2)	786 (29.2)	946 (34.7)
1-2	554 (31.6)	1523 (32.9)	577 (28.5)	912 (33.9)	862 (31.6)
≥ 3	390 (23.1)	1863(40.2)	614 (30.3)	994 (36.9)	913 (33.7)
Pediatric comorbidity scores					
0-2	1647 (94.1)	2652 (57.4)	858	2292 (85.2)	760 (27.9)
3-5	83 (4.7)	1472 (31.8)	692	329 (12.2)	1123 (41.4)

≥6	21(1.2)	499 (10.8)	476	71 (2.6)	838 (30.8)
Hospital ownership					
Non-profit /Government	1275 (72.8)	3269 (78.5)	1713 (84.5)	2407 (89.4)	2092 (76.9)
For Profit	476 (27.2)	994 (21.5)	313 (15.5)	285 (10.6)	629 (23.1)
Hospital Size					
Large	1157 (66.1)	3375 (73.0)	1457 (71.9)	2201 (81.7)	1734 (63.8)
Medium	531 (30.3)	1076 (23.3)	496 (24.5)	393 (14.6)	870 (31.9)
Small	63 (3.6)	172 (3.7)	73 (3.6)	98 (3.6)	117 (4.3)
Hospital type					
Adult	1595 (91.1)	4363 (94.4)	1764 (87.1)	2430 (90.3)	2508 (92.2)
Children	156 (8.9)	260 (5.6)	262 (12.9)	262 (9.73)	213 (7.83)
Potential health hazards related to family conditions					
No	1596 (91.2)	3469 (75.0)	1572 (77.6)	2107 (78.3)	2222 (81.7)
Yes	155 (8.9)	1154 (25.0)	454 (22.4)	585 (21.7)	499 (18.3)
Percentage of people with no high school diploma					
Median (IQR)	15.3 (9.90-21.0)	17.7 (11.7-21.2)	14.0 (9.7-19.6)	17.8 (12.4-21.1)	16.1 (11.0-21.1)
Percentage of people living below 100 FPL					
Median (IQR)	17.7 (11.7-24.1)	21.5 (15.4-28.6)	17.8 (12.6-24.0)	20.9 (15.4-28.0)	19.7 (13.8-26.1)
Percentage of unemployed person					
Median (IQR)	11.0 (9.0-14.3)	12.7 (10.0-16.3)	11.9 (9.0-24.0)	12.9 (10.6-16.1)	12.0 (9.60-15.1)

Table 2: AUC Performance comparison of the Predictive Models

Algorithms	Data Balancing	Appendicitis Mean (Error)	Asthma Mean (Error)	Seizure Mean (Error)	Sickle Cell Mean (Error)	Pneumonia Mean (Error)
RF	No SMOTE	0.54 (0.02)	0.68 (0.01)[a]	0.55 (0.24)	0.69 (0.01) [b]	0.70 (0.01)
	SMOTE	0.57 (0.02)	0.63 (0.02)	0.67 (0.01) [c]	0.67 (0.01)	0.70 (0.01)[c]
LR	No SMOTE	0.60 (0.02)[a]	0.62 (0.02)	0.67 (0.01)	0.65 (0.01)	0.70 (0.01)[b]
	SMOTE	0.57 (0.01)	0.63 (0.02)	0.68 (0.01) [b]	0.70 (0.01)[a]	0.69 (0.02)
MPNN	No SMOTE	0.55 (0.02)	0.59 (0.02)	0.63 (0.02)	0.65 (0.01)	0.66 (0.01)
	SMOTE	0.56 (0.02)	0.58 (0.03)	0.54 (0.01)	0.66 (0.03)	0.57 (0.04)
SVM	No SMOTE	0.59 (0.03)[b]	0.54 (0.01)	0.57 (0.02)	0.61 (0.01)	0.57 (0.02)
	SMOTE	0.57 (0.02)	0.65 (0.02) [b]	0.68 (0.01)	0.66 (0.01)	0.71 (0.01)[a]
AdaBoost	No SMOTE	0.52 (0.02)	0.57 (0.02)	0.62 (0.01)	0.63 (0.01)	0.65 (0.01)
	SMOTE	0.57 (0.03)	0.58 (0.02)	0.62 (0.02)	0.66 (0.01)	0.66 (0.01)
NB	No SMOTE	0.54 (0.03)	0.64 (0.01) [c]	0.69 (0.01) [a]	0.67 (0.01)	0.69 (0.02)
	SMOTE	0.57 (0.01) [c]	0.63 (0.01)	0.66 (0.01)	0.67 (0.02)[c]	0.70 (0.01)

[a]: best model
[b]: second best model
[c]: third best model
LR: Logistic Regression, NB: Naïve Bayes, RF: Random forest, SVM: Support Vector Machines with polynomial kernel, MPNN: Multilayer Perceptron Neural Network, AdaBoost: Adapting Boosting

Table 3: Multivariate Logistic Regression results for Factors Associated with Readmission by reason for admission

Variable	Appendicitis Odds ratio (95% CI)	Asthma Odds ratio (95% CI)	Seizure Odds ratio (95% CI)	Sickle Cell Odds ratio (95% CI)	Pneumonia Odds ratio (95% CI)
Age (y), n (%)					
0-5	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
5-8	0.26 (0.09-0.94), p = 0.04	0.55 (0.32-0.91), p = 0.02	0.71 (0.40-1.18), p = 0.20	0.81 (0.47-1.41), p = 0.47	0.90 (0.57-1.38), p = 0.65
8-12	0.54 (0.22-1.50), p=0.21	0.49 (0.28-0.83), p=0.01	1.08 (0.67-1.72), p = 0.73	1.38 (0.88-2.12), p = 0.16	0.76 (0.45-1.23), p = 0.28
12-17	0.47 (1.90-1.28), p =0.11	1.11 (0.70-1.76), p =0.62	1.06 (0.70-1.60), p =0.74	1.61 (1.16-2.52), p = 0.04	1.17 (0.73-1.85), p = 0.48
Gender, n (%)					
Male	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Female	0.68 (0.37-1.21), p = 0.93	1.52 (1.08-2.22), p = 0.01	1.23 (0.89-1.71), p =0.20	1.18 (0.96-1.46), p =0.10	1.00 (0.72-1.38), p =0.98
Race, n (%)					
White	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
African American	0.66 (0.23-1.72), p=0.45	0.92 (0.57-1.50), p=0.74	1.01 (0.64-1.60), p=0.94	4.45 (1.61-7.31), p=0.01	1.08 (0.69-1.69), p=0.71
Hispanic/Latin	1.37 (1.10-1.85), p=0.04	0.78 (0.57-1.5), p=0.40	1.50 (1.16-2.33), p=0.02	2.98 (0.42-5.48), p=0.08	1.08 (0.70-1.70), p=0.71
Others	0.79 (0.12-1.98), p= 0.76	0.98 (0.32-1.38), p= 0.98	1.05 (0.38-2.42), p= 0.90	1.63 (0.34-7.84), p= 0.53	2.19 (1.11-4.11), p= 0.16
Travel distance (home to hospital), n (%)					
<20 miles	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
≥ 20 miles	0.99 (0.51-1.94), p=0.94	0.94 (0.59-1.49), p=0.82	0.69 (0.44-1.07), p=0.10	1.28 (1.12-1.52), p< 0.001	0.82 (0.54-1.23), p=0.34
Disposition, n (%)					
Routine	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Post-acute care	0.65 (0.30-2.92), p = 0.62	0.97 (0.70-1.62), p = 0.20	2.71 (1.15-5.70), p = 0.01	2.46 (1.29-4.41), p < .001	3.55 (1.58-7.16), p < 0.001
Length of Stay, n (%)					
0-3 days	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
3-8 days	2.12 (1.12-3.90), p = 0.86	0.95 (0.53-1.61), p = 0.86	1.96 (1.28-2.96), p < 0.001	0.95 (0.76-1.19), p =0.71	1.07 (0.72-1.57), p = 0.70
≥ 8 days	3.80 (1.57-5.39), p = 0.15	1.97 (0.72-4.82), p = 0.15	3.40 (1.88-5.97), p <0.001	0.54 (0.38-0.77), p < 0.001	1.12 (0.65-1.84), p = 0.65
Insurance					
Public FFS	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Medicaid MCO	0.61 (0.28-1.51), p = 0.24	1.09 (0.61-2.09), p = 0.74	0.49 (0.33-0.75), p = 0.18	1.16 (0.90-1.51), p = 0.23	0.95 (0.61-1.53), p = 0.85
Private	0.39 (0.14-1.11), p =0.07	1.07 (0.50-2.33), p =0.85	0.43 (0.26-0.70), p = 0.18	0.77 (0.53-1.11), p = 0.17	0.64 (0.33-1.21), p = 0.18
Uninsured	0.15 (0.09-0.89), p = 0.08	1.19 (0.42-3.06), p = 0.72	0.81 (0.26-0.98), p = 0.41	1.27 (0.83-1.91), p =0.25	0.64 (0.26-1.44), p =0.30
Previous unplanned readmission					
0	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]

1-2	0.79 (0.40-1.91), p = 0.98	2.90 (1.80-4.94), p < 0.001	2.77 (1.85-4.10), p < 0.001	1.69 (1.24-2.31), p < 0.001	1.39 (1.07-2.27), p < 0.001
≥ 3	0.84 (0.19-2.93), p =0.47	5.41 (2.94-7.92), p < 0.001	4.69 (2.88-7.58), p < 0.001	4.40 (3.35-5.82), p < 0.001	2.02 (1.27-3.30), p < 0.001
Previous unplanned ED visits					
0	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
1-2	0.78 (0.40-1.50), p = 0.88	1.06 (0.66-1.69), p = 0.80	0.78 (0.50-1.21), p = 0.27	0.87 (0.67-1.15), p = 0.33	1.09 (0.71-1.66), p = 0.68
≥ 3	1.01 (0.38-2.39), p =0.01	1.02 (0.60-1.72), p =0.93	1.15 (0.70-1.86), p = 0.57	0.77 (0.56-1.06), p = 0.11	1.12 (0.70-1.80), p = 0.62
Pediatric comorbidity scores					
0-2	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
3-5	1.38 (0.56-3.16), p = 0.75	1.08 (0.26-3.02), p = 0.85	1.04 (0.69-1.56), p = 0.84	0.94 (0.68-1.29), p = 0.73	1.55 (0.99-2.51), p = 0.16
≥6	1.85 (0.85-3.79), p = 0.98	1.75 (1.05-2.84), p = 0.02	1.26 (1.08-1.56), p = 0.01	1.74 (1.24-3.11), p = 0.02	3.51 (2.29-5.54), p < 0.001
Hospital ownership					
Non-profit /Government	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
For Profit	2.09 (0.93-4.42), p = 0.06	0.93 (0.49-1.68), p = 0.82	0.93 (0.44-1.83), p = 0.84	1.11 (0.75-1.62), p = 0.57	1.26 (0.70-1.22), p = 0.41
Hospital Size					
Large	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Medium	0.38 (0.13-1.01), p = 0.06	0.61 (0.17-1.69), p = 0.68	0.92 (0.40-2.12), p = 0.86	1.07 (0.61-1.82), p = 0.80	0.74 (0.40-1.33), p = 0.32
Small	0.86 (1.33-3.08), p = 0.84	0.43 (0.15-1.22), p = 0.39	0.96 (0.36-2.21), p = 0.92	0.39 (0.14-0.87), p < 0.01	1.23 (0.48-2.72), p = 0.62
Hospital type					
Adult	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Children	0.13 (0.04-0.45), p < 0.001	0.43 (0.15-1.22), p =0.82	1.20 (0.45-3.20), p = 0.71	0.98 (0.51-1.86), p = 0.96	0.43 (0.20-0.92), p < 0.001
Potential health hazards related to family conditions					
No	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Yes	0.74 (0.21-1.89), p = 0.56	0.98 (0.64-1.49), p = 0.11	1.24 (0.84-1.82), p = 0.25	1.22 (1.08-1.35), p = 0.01	1.07 (0.72-1.57), p = 0.71
Percentage of people with no high school diploma					
1% increment	1.01 (0.96-1.06), p = 0.59	0.99 (0.95-1.03), p = 0.71	1.01 (0.98-1.05), p = 0.25	0.99 (0.97-1.02), p = 0.72	0.97 (0.96-0.99), p = 0.02
Percentage of people living below 100 FPL					
1% increment	0.99 (0.93-1.05), p = 0.80	0.99 (0.95-1.02), p = 0.62	0.99 (0.96-1.03), p = 0.80	0.97 (0.95-0.99), p = 0.03	1.02 (0.99-1.04), p = 0.12
Percentage of unemployed person					
1% increment	0.97 (0.88-1.07), p 0.58	1.06 (1.01-1.12), p 0.03	0.97 (0.91-1.03), p = 0.28	1.03 (0.99-1.07), p = 0.13	0.97 (0.92-1.03), p = 0.35

Appendix F: A Multi-State Decomposition Analysis of Cesarean Rate Variations, Associated Outcomes, and Financial Implications in the United States

Appendix F shows the manuscript titled, " A multi-state decomposition analysis of cesarean rate variations, associated health outcomes, and financial implications in the United States ", which is under review in American Journal of Perinatology.

A multi-state decomposition analysis of cesarean rate variations, associated health outcomes, and financial implications in the United States

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Abstract

Objectives: Cesarean rates vary widely across the United States (U.S.) states; however, little is known about the causes and implications associated with these variations. The purposes of this study were to quantify the contribution that patient and hospital characteristics in explaining the differences across states and investigate the associated health outcome of cesarean variations.

Study Design: Using the Hospital Cost and Utilization Project State Inpatient Databases, this retrospective study included all non-federal hospital births from Wisconsin, Florida, and New York. A non-linear extension of the Oaxaca-Blinder method was used to decompose the contributions of differences in characteristics to cesarean variations between these states. The risk factors for cesarean delivery were identified using separate multivariable logistic regression analysis for each State.

Results: Overall (46.57–65.45%) of the variation between states could be explained by the variables, and major contributors were patient demographics, previous cesareans, hospital markup ratios, and social determinants of health. Cesarean delivery was significantly associated with higher postpartum readmissions and unplanned emergency department visits, greater lengths of stay, and hospital costs across all states.

Conclusion: Although a proportion of variations in cesarean rates can reasonably be expected given the differences in risk factors, the remaining unexplained variations suggest differences in practice patterns and imply potential quality concerns. Since non-clinical factors are likely to play an important role in cesarean variation, we recommend targeted initiatives increasing access to maternal care and improving maternal health literacy.

Key Points

1. Cesarean rates vary widely almost two folds within US states.
2. (~46.57–65.45%) of the variations explained by the differences in risk factors.
3. Patient race, hospital characteristics, and social determinants comprised the major proportion of explained variation.
4. Cesarean risk factor varies widely particularly patient comorbidity and social determinants of health across US states.
5. Significant potential cost savings for Medicaid if the unnecessary cesarean deliveries are reduced.

Introduction

Cesarean delivery is the most commonly performed inpatient surgical procedure in the United States.[1] Cesarean delivery commonly known as C-section surgical procedure is performed through incisions in the abdomen and uterus to deliver a baby. The cesarean delivery rate increased by 60% from 1996 to 2009, accounting for nearly one-third of births, and its use remains almost same.[2,3] Unlike most other developed countries, Cesarean rates in the United States exceed the World Health Organization recommended threshold of 10–15% and yet, stand out among other high-income countries where pregnancy-related deaths are declining.[4,5] Studies reported that cesarean rates greater than 15% were neither correlated to higher maternal nor child mortality, nor low weight-at-birth. [6] Cesarean delivery is an important, potentially life-saving intervention, especially for high-risk pregnancies (e.g., previous cesarean, prolonged labor) and mother with multiple comorbidities.[7] While common but yet complicated, cesarean delivery may carries short and long-term risks for both the mother and child.[8,9] Cesarean patients have greater chances of infection, blood clot, the need for emergency hysterectomy, post-discharge complication and future problematic pregnancies compared to those using vaginal delivery.[7,10] Moreover, studies reported child born by non-medically indicated cesarean have a higher prevalence of pulmonary disorders up to the age of 12 years (Odd Ratio 1.21, 1.11 to 1.32) and obesity up to the age of 5 years (OR 1.59, 1.33 to 1.90) than those born by vaginal delivery.[8,11,12] Nonetheless, cesarean delivery is also costlier and involves more resources than vaginal delivery.[13,14] The rise in cesarean procedures coupled with adverse outcomes and complications has substantial cost implications for both public and private health insurers. In 2009, state Medicaid programs paid more than $3 billion for cesarean deliveries.[15] Therefore, it has become a major policy concern for insurers, clinicians, and policymakers. The Healthy People 2020 initiative from the U.S. Department of Health and Human Services has set public health goals that recommend a 10% reduction in both primary and repeat cesarean rates to 23.9% and 81.7%, respectively.[16]

The unprecedented rise in the cesarean rate has commonly been attributed to factors such as a higher rate of maternal comorbidities (e.g., preterm labor, obesity) that may necessitate cesarean delivery as well as patients' personal and socioeconomic characteristics.[17–19] However, evidence indicates that these factors do not fully account for the wide differences in cesarean rates observed between hospitals, health insurers, and communities.[20,21] Variations in cesarean rates are an important indicator of maternal care quality and may signal the underuse or overuse of this lifesaving procedure, both of which can be clinically harmful [7,22]. In particular, unexplained variations in US states might indicate an overuse of unnecessary cesareans in certain states. These unexplained higher cesareans and associated incremental cost can strain healthcare budget particularly for some states where State Medicaid (e.g., Florida, New York) covered more than 50% of the pregnancy. [14,21,23] Therefore, Understanding the extent and causes of these variations in US states may provide opportunities for reducing the use of cesarean delivery. Thus far, studies have been limited to cesarean variations seen in hospitals, Medicare spending, and among health insurers rather than through a state-level peer-to-peer analysis.[20,24–26] Information about what causes variations across U.S. States , whether resulting from differences in patient and hospital characteristics is not clear.

Understanding the causes of inter cesarean variations and their impact on outcomes is important for several reasons. First, reducing the number of unnecessary cesareans has become a priority for healthcare experts, and a targeted approach to achieving these reductions can focus on states with exceptionally high cesarean rates.[16,27] Furthermore, the adoption of these strategies requires an understanding of the causes of state-level cesarean variations. Second, several state Medicaid agencies have adopted or plan to adopt different educational and payment-based cesarean reduction strategies.[28] Since each state has unique public healthcare programs with distinct eligibility requirements, understanding variations through peer-to-peer comparisons can help policymakers in identifying opportunities to improve maternal care.[29] Third, as the primary public insurer Medicaid, states have significant policy leverage over maternal care through Medicaid coverage and benefit structure. Understanding the realities of existing differences in cesarean rates and associated outcomes is crucial to state policymakers for developing new action plans or restructuring state Medicaid programs.[30,31] Therefore, this study aimed to answer the following questions. What are the clinical and non-clinical factors that are responsible for cesarean variation across US states and how much variation this factor contributes? Second,

how the risk factors and cesarean associated outcome varies across the US States? We hypothesized that the variations in cesarean rates is influenced by each state's unique patient population demographics, clinical characteristics, and healthcare infrastructures.

Material and methods

Data source and study design

This study examined hospital admissions data from January 1, 2014 to December 31, 2014 from the State Inpatient Databases (SID), which are available from the Agency for Healthcare Research and Quality's Healthcare Cost and Utilization Project (HCUP). Three states were selected for the analysis: Wisconsin, Florida, and New York. These states were chosen based on the availability of all-payer admission data as well as their variations in cesarean rate, distinct population demographics, and geographical differences, which helped them serve as a proxy for a nationwide comparison of cesarean rates. Other states were not included due to time and cost restraints in obtaining each state's datasets. The HCUP SID contains admission information for all payers and uninsured patients in nonfederal hospitals. Our analysis was limited to the single year 2014 State Inpatient dataset for several reasons. First, considering a single calendar year delivery-related hospitalization may increase homogeneity for each state dataset since Hospitals and health service providers generally undergo major changes in treatment protocols and other management early in the calendar year. Second, cesarean rates in Florida, Wisconsin, and New York remain almost similar starting from the year 2014. Third, starting from the year 2014, Several States (e.g., New York) started to implement Medicaid Affordable care Expansion while some states (e.g., Florida and Wisconsin) were not. Therefore, analysis of the 2014 calendar year dataset in different states with unique healthcare systems would provide an opportunity to analyze the causes and implications of State cesarean variation.

Obstetric delivery-related admissions were identified from diagnosis and procedure codes using the widely recognized stepwise methodology.[32] Patient discharges with an abortive outcome, stillbirth, residential address outside the state, against medical advice, and in-hospital mortality were excluded from the dataset. Each admission had a unique patient identifier that was used to track patients across hospitals and could therefore be used to identify unplanned readmissions and emergency department (ED) revisits. Information on hospital structures was obtained through the unique identifier hospital linkage between the HCUP SID and American Hospital Association Annual Survey. Data on the patients' social determinants were derived from the American Community Survey (ACS) by linking patient ZIP codes though the Uniform Data System (UDS) Mapper. The UDS Mapper crosswalk is a publicly available resource supported by the U.S. Health Resources and Services Administration and has been validated in prior studies.[33,34] The final datasets for the Florida, New York, and Wisconsin cohorts contained 187,607, 221,712, and 62,393 hospital discharges, respectively, that were used for further statistical analysis. The Institutional Review Board IRB approval was not required for this study because the HCUP does not involve human subjects and the patients' personal information was de-identified.

Outcome measures and variables

Cesarean delivery-related hospital admissions were identified using International Classification of Diseases, Ninth Revision (ICD-9), procedure codes (740. **, 741**, 742. **, 744. **, 749. **) as well as the diagnosis-related group (DRG) codes 765 and 766. Cesarean delivery rates were calculated as the percentage of livebirth cesarean deliveries among all obstetric deliveries. Low-risk deliveries were identified for all terms as singleton, vertex, and live birth deliveries without prior cesarean and without high- risk diagnoses [1]. The demographic variables included in our study were age (≤ 18, 18-30, 30–40, or ≥ 40 years) and race (African American, White, Hispanic, or other). Other patient admission related factors included admission day (weekend or weekday) and admission type (elective or non-elective). Hospital level covariates were teaching hospital status, hospital markup ratio, and hospital bed size (0–299 and ≥ 300 beds). The patients' socioeconomic characteristics were payer information (public, private, or uninsured) and ZIP code income quartile (0–25, 25–50, 50–75, and 75–100). For maternal comorbidity variables, we evaluated 24 common comorbidities to classify comorbidity risk status [35] These variables were then weighted and summed to generate a maternal comorbidity score. These comorbidity scores were further categorized into three patient groups (0 [lowest risk], 1 or 2, or >2 [highest]).

The obesity/overweight and previous cesarean indicator was included in this study as separate comorbidity variables since it was not included in calculating the comorbidity score. The social determinants of health (SDH) variables included in this study were poverty, education, and employment data. The SDHs variables included in our study were the percentages of people living 300% above the federal poverty level, the adult population with at least a bachelor's degree, and the female population with employment, respectively. These variables were available at the ZIP Code Tabulation Area level, a generalized area representation of ZIP codes used by the U.S. Census.[36]

Our outcome variables were unplanned postpartum readmission, length of stay (LOS), hospital cost, and unplanned ED visit. Postpartum hospital readmission was defined as an admission within 42 days (6 weeks) after the date of delivery admission.[37] Readmission rates for the delivery groups and individual states were calculated by dividing the number of readmissions by the number of delivery admissions. Hospital costs were estimated as the product of hospital charges and cost-to-charge ratio after adjusting with the geographic adjustment factor.[38] Unplanned ED visits were calculated as a binary (yes/no) variable for any return to the ED within 42 days of hospital discharge.

Statistical analysis

All delivery-related hospitalizations were categorized into two groups of cesarean and vaginal delivery for each state cohort. Multiple imputations were conducted using a chained equation for the race variable to deal with the missing values. Separate state-specific descriptive analyses were performed for cesarean vs vaginal delivery groups using bivariate analysis. A Fairlane modification of the Blinder-Oaxaca decomposition technique was used to examine the influence of the differences in the observed characteristics on cesarean rate variations across states.[39] This decomposition technique has been widely used in prior studies to examine the impact of group differences on the outcome, particularly in social and healthcare disparity analyses.[40,41] The Blinder-Oaxaca decomposition can be able to explain how much of the difference in mean outcomes across two groups (e.g., Cesarean delivery in Florida and Wisconsin) is due to group differences in the levels of explanatory variables (e.g., For Race, the proportion of Hispanic mother in Florida and Wisconsin). This decomposition approach disaggregates simultaneously the unadjusted difference into two proportions (1) Explained variation that can be explained by observed characteristics (2) Unexplained variation, the residual difference that cannot be explained by differences in observed characteristics. The Fairlie approach involves the estimation of a pooled regression model for each subgroup, estimate and store the estimated coefficients, and then substitute the means for each variable.

For example, to quantify the contribution of insurance type difference on cesarean rate variation between Florida and Wisconsin, the mean outcome (Here, Y for cesarean rate) difference between the mean dependent variable for the insurance type (Here, P for public insurance and C for commercial type) can be decomposed as

$$\Delta\bar{Y} = \bar{Y}^P - \bar{Y}^C = \left(\bar{X}^P\hat{\beta}^P - \bar{X}^C\hat{\beta}^C\right) = \hat{\beta}^P(\bar{X}^P - X^C) + \bar{X}^c(\hat{\beta}^P - \hat{\beta}^C)$$

where, $\Delta\bar{Y}$ is the unadjusted cesarean rate difference between Florida and Wisconsin, $\bar{X}^P$ and $\bar{X}^C$ are row vector of mean values of independent variables, $\hat{\beta}^P$ and $\hat{\beta}^C$ are is a vector of coefficient estimates for public and private insurance, respectively. The first term of the final equation is the expanded variation due to between-group differences in covariates and unexplained variation due to differences in the regression parameters. The explained and unexplained variation contributed by the covariates was expressed as a percentage of the unadjusted difference.

Three separate multivariate logistic regression models with robust Standard Errors (SEs) were used to identify significant factors responsible for cesarean delivery in each State. To examine the differences in outcomes associated with modes of delivery, separate multivariable linear regressions with hospital random factors and robust SEs were performed for each state. The categorical outcomes of unplanned readmission and ED visits were compared using multivariate logistic regressions with a separate model for each outcome. Generalized linear models with log-link exponential families were used to assess the difference in hospital costs and LOS. All statistical analyses were performed using RStudio, and a two-sided P-value less than 0.05 was considered

statistically significant. Modified Hosmer-Lemeshow and Pearson chi-square tests along with a pseudo r^2 were used to check the goodness-of-fit for each regression model.[42]

Results

A total of 2741984, 2367188, and 602,982 hospital visits were analyzed for Florida, Wisconsin, and New York, respectively. Among those who met the inclusion criteria, 187,607 (6.84%), 221,712 (9.36%), and 62,393 (10.34%) discharges were identified, and among these, 73,420 (39.10%), 74,343(33.51%), and 16,355 (26.21%) were cesarean deliveries for Florida, Wisconsin, and New York, respectively. S1-S3 Tables summarize patient and hospital characteristics (frequencies and interquartile range) for cesarean and vaginal delivery for each state cohort. Patient demographics and other characteristics varied widely across the states. Maternal age was higher in New York than in Wisconsin and Florida. The proportion of White mothers in Wisconsin (71.8) was higher than New York (48.3%) and Florida (46.6 %). Most of the births (~50%) were covered by public payers except in Wisconsin. Overall, postpartum readmission rates for Florida, Wisconsin, and New York were 1.72%, 1.12%, and 1.18%, respectively. Cesarean delivery rates (Figure 1) varied widely across hospitals in all three states, with rates that ranged nearly ~2.5–3.7 fold, from low (~14–21%) to high (~37–63%). However, cesarean rate variations across hospitals for lower-risk pregnancies were comparably lower than the overall cesarean rate (Figure 2).

Decomposition of the differences in cesarean rates across states

The results of the decomposition analyses are presented in Table 3. The raw differences in cesarean rates for Florida vs Wisconsin, Florida vs New York, and New York vs Wisconsin were 12.9%, 5.5%, and 7.3%, respectively. The overall contribution of the variations explained by the variables differed (Florida vs Wisconsin 58.91%; Florida vs New York 65.45%; New York vs Wisconsin 46.57%) across groups. Previous cesarean section was accounted for a larger proportion (~18.59–25.61%) of the explained variation for all paired groups. Other maternal clinical factors, multiples, gestational hypertension, and pericardial effusion also significantly explained the differences across paired groups. The demographic distribution of the mothers' ethnicity also accounted for (~7.51–14.82%) variations in the cesarean rate. The differences in hospital markup ratios explained a substantial proportion of the variations (~20.10–22.41%), particularly when compared with Florida. Furthermore, the results show that the SDH variables explained a significant proportion (~7.60–23.77%) of the differences across the states. Among the social determinants, the contributions of household income and female employment status were significant and noteworthy. By excluding the SDH variables from the model, the proportion of the difference explained by the model was reduced to (~29.15–34.26%). The results suggest that the SDH variables play a significant role in the variations in the cesarean rate.

Variation in cesarean risk factors across US States

Multivariate analyses for the factors influencing cesarean delivery are shown in Table 1. Based on these analyses, the factors that were more likely to be associated with cesarean birth were older age, non-White mothers (except in Wisconsin), being admitted on weekdays, elective admissions, being privately insured, and hospitals located in micro/rural areas. We found that African American and Hispanic mothers were associated with a higher risk for cesarean delivery than white mothers except in Wisconsin, where white mothers were associated with a higher risk for cesarean than other groups. Patients with a higher ZIP-code level income quintile were more likely to have cesarean births in New York. However, patient ZIP-code level was not a significant factor in the other two states.The presence of a higher maternal comorbidity score was also a strong predictor (e.g., Odds Ratio [OR],13.5; 95% Confidence Interval [CI], 13.2-13.9 for ≥ 3 vs 0 in Florida) of cesarean delivery over vaginal birth. The most frequent pathologies associated with cesarean births included previous cesarean, gestational hypertension, asthma, prehypertension, pericardial effusion, and multiple gestations (Table 2). Patients with previous cesarean and multiple gestations had substantially higher rates ($\geq 65\%$) of cesarean delivery. The cesarean rate for patients with a previous cesarean birth was significantly higher in Florida (94.5%) than in Wisconsin (84.0%) and New York (78.1%). Patients who underwent admission in teaching affiliated, higher markup ratio, and smaller size hospitals had a higher likelihood of cesarean birth except in Wisconsin.

Variation in cesarean outcome across US States

In the multivariate analysis adjusted for all covariates, cesarean delivery resulted in higher odds (33% higher in Wisconsin, 47% higher in Florida, and 61% higher in New York) of experiencing post-partum readmission as compared with vaginal delivery. Furthermore, patients who underwent cesarean delivery had a slightly higher likelihood (12% higher in Wisconsin, 8% higher in Florida, and 7% higher in New York) to experience an unplanned ED visit than those discharged after vaginal delivery. The overall LOS in all cohorts was longer ($p < 0.01$, all cohorts) in cesarean delivery (median LOS of 3 days, all cohorts) than vaginal delivery (median LOS of 2 days, all cohorts). Finally, hospital costs were significantly higher ($p < 0.01$, all cohorts) in cesarean delivery (median cost $3524 vs. $6369 for Wisconsin; $2708 vs. $4794 for Florida; $3990 vs. $6203 for New York) than vaginal delivery. The results of the outcome comparisons for each state are shown in Table 4.

Economic implications

The total hospital cost for cesarean deliveries in Wisconsin, Florida, and New York were $157.85 million (median cost $6369 with Interquartile range, [$5158-$6369]), $496.52 million (median cost $4794 with Interquartile range, [$3721-$6384]), and $562.76 million (median cost $6203 with Interquartile range, [$4728-$8123]), respectively. Total postpartum readmission hospital costs in Wisconsin, Florida, and New York were $4.63 million (median cost $7125), $21.53 million (median cost $6259), and 37.82 million (median cost $6145), respectively. Similarly, unplanned ED visits cost Wisconsin, Florida, and New York $2.13 million, $13.41 million, and 12.46 million, respectively. The low-risk cesarean rates for Wisconsin, Florida, and New York were 20.12%, 26.27%, and 24.51%, respectively. If low-risk cesarean delivery had been reduced by at least 10%, the potential healthcare savings in Wisconsin, Florida, and New York in 2014 would have been $11 million, $52 million, and $32 million, respectively. Savings in healthcare spending were calculated as the cumulative effect of reductions in healthcare expenses for cesarean delivery and respective unplanned outcomes (readmissions and ED visits). Specifically, Florida and New York would have seen potential savings in Medicaid expenditures in 2014 of $31 million and $19 million, respectively.

Discussion

Using the HCUP SID, our study made three important findings. First, overall (~46.57–65.45%) the cesarean variations across states could be explained by the variables. The cesarean variations explained by our study are considerably greater than those of a prior study (~30.7–43.7%) in the United States [43]. Patient race, previous cesarean birth, hospital markup ratio, and social determinants explained the largest proportion of the differences in state cesarean rates. Second, risk factors associated with cesarean delivery varied widely across US states. Besides, cesarean delivery associated health outcomes and hospital expenditure were also varied across US states. Finally, there is significant potential cost savings for all three states, particularly for public insurers, if the number of the unnecessary cesarean deliveries is reduced. Altogether, this study holistically discusses the causes and associated outcomes of the persistent cesarean rate variations across the US states.

Across all three states, older maternal age found significant risk factors and determinants of cesarean variation similar to reported in prior studies.[20,44–46] Increased rate of cesarean among older women across all states could be explained by non-pregnancy-related medical conditions and other non-clinical factors such as socioeconomic status, parental anxiety, previous infertility, and physicians' beliefs.[45,47] Consequently, the difference in maternal age distribution explained 12.5% of the total differences in the cesarean rate between New York and Wisconsin. Furthermore, we also observed a risk-adjusted increased risk of cesarean among African American and Hispanic women relative to White mothers, except in Wisconsin.[44] This finding is likely to be related to the cross-cultural differences and a higher prevalence of high-risk cesarean demographic subgroups (e.g., Latin Americans and West Indian Americans in Florida and New York), which may contribute to the increased cesarean rate among Hispanic mothers.[48,49] In our novel analysis, we found an intriguing variation of clinical conditions related to cesarean risk factors (e.g., previous cesarean, multiples births, and overweight/obesity) across US states. These variations are likely to be caused by the persistent racial and ethnic disparities in cesarean delivery risk and social determinants of health, particularly among women with pre-pregnancy overweight and previous cesarean birth.[50–53] These findings for disparities in risk-adjusted cesarean delivery across the US states reinforce the need for state-specific intervention addressing the tenacity of racial disparities in obstetric care and birth outcomes.

Implementing State need specific interventions, such as midwife/doula-led continuity of care in rural areas, antenatal education in targeted community , and training for patients with first time pregnancy can potentially reduce the unnecessary cesarean delivery and associated adverse outcomes.[54,55]

Our results of the fewer likelihood of cesarean associated with public insurance than those with private insurance suggest potential overuse across all three states.[24] Besides, striking variations in hospital cesarean rates for lower-risk pregnancies (Figure 2) indicates that patient risk factors probably do not provide a full explanation for these differences across states. Consequently, we found hospital-level risk factor, markup ratio solely explained higher than 20% of the total variation between Wisconsin and other States. This variation may be caused by the higher likelihood of cesarean associated with a higher markup ratio except in Wisconsin where most of the hospitals are not for profit and Church operated compared with Florida and New York. The higher financial incentive gap between cesarean and vaginal delivery moderately increases the likelihood of cesarean for low-risk pregnancies but has the greatest effect on women who are high risk or close to the high-risk margin.[56] Financial strategies, including incentivizing institutions that perform the desired actions/outcomes or penalizing hospitals for high cesarean rates, could also be considered but require monitoring for unintended consequences.[18,21] Our study showed variation in postnatal readmissions, and unplanned ED visits across the US states. This finding is likely related to the observed racial and ethnic disparities in readmissions after childbirth.[57] Given that cesarean delivery rates are correlated significantly with higher spending and adverse outcomes, reducing unnecessary cesareans through clinical and non-clinical interventions can not only potentially save significant healthcare costs but also reduce post-natal adverse events.[43,54,55]

Our study has various limitations, most of which are related to it being a retrospective analysis of large administrative claim datasets. First, the HCUP SID databases are constructed of ICD-9 CM codes used for hospital claims, and some inaccuracy in the coding of procedures and diagnoses may be excluded. Second, the HCUP dataset does not include information for federal hospital discharges and non-hospital births (e.g., birth center deliveries and home births). However, the proportion of these out-of-hospital births are very small compared to hospital births and would not affect our estimation.[58] Third, hospital costs were derived from reported charges using hospital-level cost-to-charge ratios and may contain inaccuracies due to providers not always accurately knowing the costs of care. More precise cost estimations, such as detailed hospital charges and department-level cost to charge ratios, might have improved the accuracy of our findings. Fourth, the analyses of three specific states may prevent the generalizability of these results to other states. These three states were chosen because of their unique healthcare systems, diverse demographic distributions, and varying geographic locations to serve as an approximation of a nationwide comparison of cesarean rate differences. Finally, there may also be other factors that can explain the unexplained differences in the prevalence of cesarean across states. These include pregnancy weight gain, fertility treatments, hospital malpractice liability, and the staff present at delivery.[57,59] However, fertility treatments contribute to a very small percentage of all cesarean deliveries and are most prevalent in women with private insurance.[20] Besides, available malpractice payment data from the National Practitioner Data Bank[60] suggest that per person malpractice payments for the three states were similar and medical malpractice liability is not likely a driver of the wide variations we detected.[61]

Conclusions

Understanding cesarean variations can create important health and cost implications for state and federal public health agencies, Medicaid programs, Medicaid managed care plans, and the four million American families that bring a newborn home from the hospital every year. The variations in cesarean rates across three states were influenced by the differences in both clinical and non-clinical factors. The variation in cesarean variations in risk factors across states most likely because of the persistence of racial disparities in maternal care and social determinants of health . Although some variations in cesarean rates can reasonably be expected given the differences in patient risk factors, the remaining unexplained variations and the scale of hospital-level variations for low-risk births suggests differences in practice patterns across hospitals and signals potential quality concerns. Increased healthcare expenditures and worse outcomes associated with cesarean delivery endorse the need for potential interventions if cesarean delivery is clinically unnecessary. Since non-clinical factors are likely to play an important role in an increased cesarean rate, we recommend state specific interventions, including

improving access to maternal care, training for patients for state-specific high-risk groups (e.g., Hispanic/Latino), and restructuring the reimbursement schemes of for-profit hospitals (e.g., bundled payment, managed care).

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List of Figures

Figure 1. Distribution of total cesarean rates in hospitals across Wisconsin, Florida, and New York state

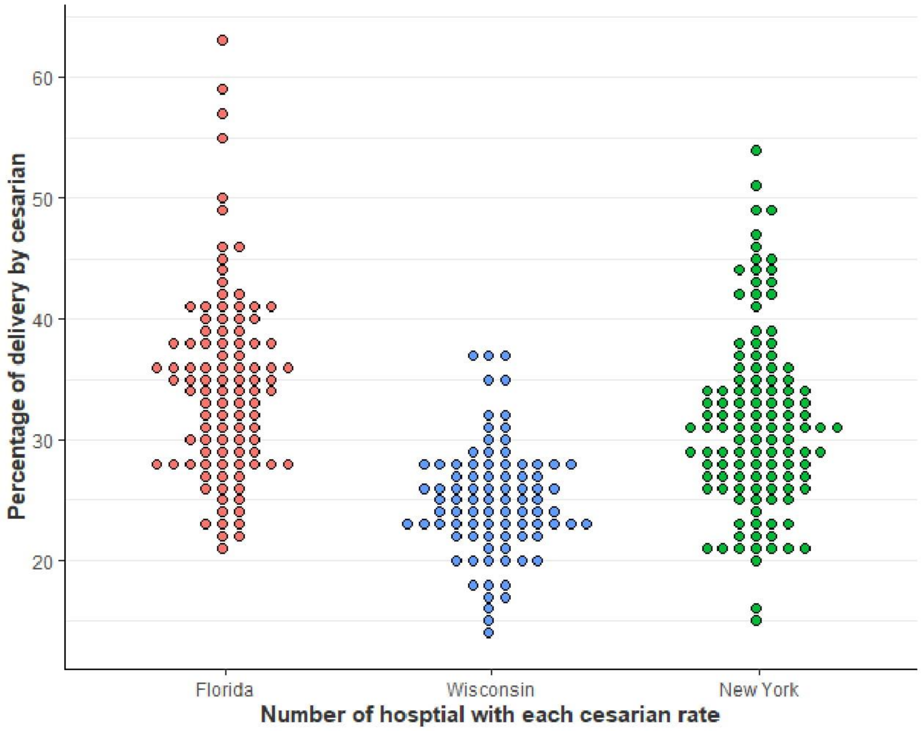

Figure 2. Distribution of cesarean rates in hospitals among lower-risk pregnancies Wisconsin, Florida, and New York state

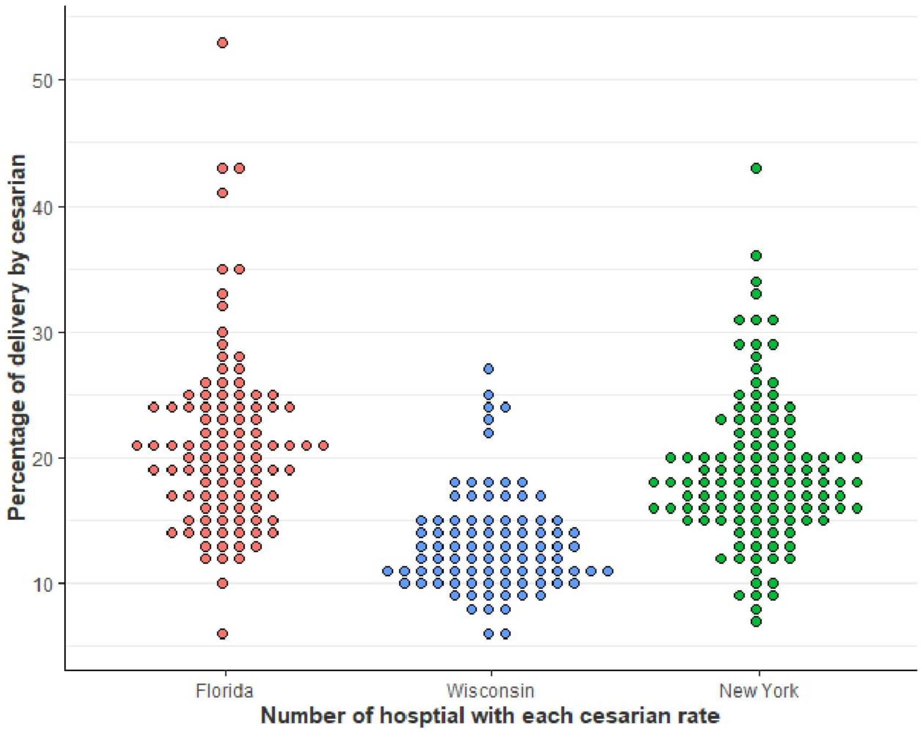

Table 1. Multivariate logistic regression analyses for factors associated with cesarean delivery

	Multivariate Odds ratio (95% CI), P value		
Variable	Wisconsin	Florida	New York
Demographic characteristics			
Age (y)			
18-30	1 [Reference]	1 [Reference]	1 [Reference]
≤ 18	0.75 (0.65-0.87), p <0.01	0.68 (0.63-0.72), p < 0.01	0.62 (0.58-0.67), p < 0.01
30-40	1.25 (1.20-1.30), p <0.01	1.31 (1.28-1.34), p < 0.01	1.33 (1.30-1.36), p < 0.01
≥40	1.89 (1.61-2.23), p <0.01	1.99 (1.84-2.15), p < 0.01	2.02 (1.90-2.14), p < 0.01
Race			
White	1 [Reference]	1 [Reference]	1 [Reference]
African American	0.87 (0.81-0.95), p < 0.01	1.16 (1.12-1.19), p < 0.01	1.43 (1.39-1.48), p < 0.01
Hispanic	1.02 (0.93-1.11), p = 0.43	1.58 (1.54-1.64), p < 0.01	1.34 (1.29-1.38), p < 0.01
Others	0.96 (0.88-1.04), p = 0.61	1.21 (1.15-1.26), p < 0.01	1.38 (1.31-1.40), p < 0.01
Admission characteristics			
Admission type			
Non-elective	1 [Reference]	1 [Reference]	1 [Reference]
Elective	1.43 (1.37-1.50), p < 0.01	1.56 (1.53-1.60), p < 0.01	1.37 (1.34-1.41), p < 0.01
Weekend			
No	1 [Reference]	1 [Reference]	1 [Reference]
Yes	0.68 (0.64-0.71), p < 0.01	0.68 (0.66-0.70), p < 0.01	0.64 (0.63-0.66), p < 0.01
Clinical characteristics			
Maternal comorbidity score			
Low (0)	1 [Reference]	1 [Reference]	1 [Reference]
Medium (1-2)	7.26 (6.85-7.69), p < 0.01	6.31 (6.12-6.51), p < 0.01	6.22 (6.04-6.40), p < 0.01
High (≥ 3)	7.89 (7.53-8.26), p < 0.01	9.93 (9.67-10.2), p < 0.01	7.82 (7.64-8.01), p < 0.01
Obesity/Overweight			
No	1 [Reference]	1 [Reference]	1 [Reference]
Yes	1.88 (1.76-2.01), p < 0.01	1.56 (1.49-1.63), p < 0.01	1.56 (1.50-1.62), p < 0.01
Socioeconomic characteristics			
Household income Percentile			
0-25	1 [Reference]	1 [Reference]	1 [Reference]
25-50	1.08 (1.01-1.16), p = 0.01	1.02 (0.99-1.05), p = 0.02	1.13 (1.09-1.18), p < 0.01
50-75	1.07 (0.99-1.16), p = 0.11	0.98 (0.95-1.01), p = 0.64	1.10 (1.06-1.15), p < 0.01
75-100	0.93 (0.85-1.02), p =0.24	1.04 (1.00-1.12), p =0.04	1.22 (1.18-1.27), p < 0.01
Insurance			
Public	1 [Reference]	1 [Reference]	1 [Reference]
Private	1.20 (1.14-1.26), p < 0.01	1.21 (1.18-1.24), p < 0.01	1.23 (1.20-1.26), p < 0.01
Uninsured	1.07 (0.93-1.24), p = 0.30	0.94 (0.89-1.01), p = 0.07	1.05 (1.00-1.11), p = 0.04
Social Determinants			
Percentage of people over 300% FPL			
Per 1% increase	1.01 (1.00-1.02), p < 0.01	0.98 (0.98-0.99), p < 0.01	1.01 (1.00-1.01), p < 0.01
Percentage of people with bachelor's degree			
Per 1% increase	0.98 (0.98-0.99), p < 0.01	1.01 (1.01-1.02), p < 0.01	0.98 (0.98-0.99), p < 0.01
Percentage of female employment			
Per 1% increase	0.99 (0.99-1.00), p =0.26	0.99 (0.98-0.99), p <0.01	1.00 (1.00-1.01), p < 0.01
Hospital characteristics			

Teaching hospital			
No	1 [Reference]	1 [Reference]	1 [Reference]
Yes	0.59 (0.54,0.64), $p < 0.01$	1.11 (1.07-1.14), $p < 0.01$	0.92 (0.90-0.95), $p < 0.01$
Hospital size			
Over 300	1 [Reference]	1 [Reference]	1 [Reference]
0-299	0.68 (0.62-0.75), $p < 0.01$	1.16 (1.12-1.19), $p < 0.01$	1.15 (1.12-1.19), $p < 0.01$
Markup ratio			
Per 1 increase	1.04 (1.03-1.05), $p < 0.01$	0.92 (0.89-0.94), $p< 0.01$	1.03 (1.02-1.05), $p < 0.01$

Table 2. Top comorbidity pathologies of total and cesarean delivery admissions

State	Wisconsin N=62393		Florida N=187607		New York N=221712	
Diagnosis category	Total (%)	Cesarean delivery N (%)	Total (%)	Cesarean delivery N (%)	Total (%)	Cesarean delivery N (%)
Previous cesarean delivery	9306 (14.1)	7743 (83.2) *	36733 (19.6)	34638 (94.3) *	38680 (17.4)	29100 (86.0) *
Gestational hypertension	2467 (4.0)	770 (31.2)	7629 (4.1)	3281 (43.0)	6751 (3.0)	1744 (38.7)
Asthma	4032 (6.5)	1287 (31.9)	7035 (3.7)	3082 (43.4)	11370 (5.1)	3216 (38.9)
Prehypertension	1053 (1.7)	467 (44.3)	4855 (2.6)	2888 (59.5) *	4464 (2.0)	1911 (54.5) *
Drug dependence	1227 (2.0)	335 (27.3)	4802 (2.6)	1789 (37.3)	4796 (2.2)	959 (26.3)
Pericardial effusion	1246 (2.0)	495 (39.7)	4700 (2.5)	2457 (52.3) *	3783 (1.7)	1483 (58.3) *
Multiple gestations	1150 (1.8)	743 (64.6) *	3494 (1.9)	2448 (81.5) *	4647 (2.1)	2981 (76.1) *
Severe preeclampsia	1012 (1.6)	578 (57.1) *	3247 (1.7)	2400 (73.9) *	4141 (1.9)	1929 (61.9)
Diabetes mellitus	686 (1.1)	385 (56.1) *	1925 (1.0)	1335 (69.4) *	2099 (0.9)	1006 (63.5) *
Placenta previa	355 (0.6)	281 (79.2) *	1090 (0.6)	918 (84.2) *	1558 (0.7)	1203 (87.5) *
Sickle cell anemia	120 (0.2)	35 (29.2)	543 (0.3)	234 (43.1)	543 (0.4)	260 (39.9)
Valvular heart disease	91 (0.1)	26 (28.6)	533 (0.3)	262 (49.2)	533 (0.3)	198 (45.4)
* conditions with cesarean rates above the overall average of 50%						

Table 3. Results of decomposition analyses on caesarean rate pairwise comparison among the sates

	Florida vs Wisconsin		Florida vs New York		New York vs Wisconsin	
	Absolute difference	Contribution (%), p value	Absolute difference	Contribution (%), p value	Absolute difference	Contribution (%), p value
Overall	0.129	100	0.055	100	0.073	
Explained	0.076	58.91	0.036	65.45	0.034	46.57
Unexplained	0.053	41.09	0.033	34.54	0.041	53.43
Demographic characteristics						
Age (y)						
18-30 [Reference]						
≤ 18	-0.001	-0.39, p <0.01	-0.003	-4.59, p <0.01	0.002	2.86, p <0.01
30-40	0.001	0.89, p <0.01	-0.001	-1.53, p <0.01	0.002	6.30, p <0.01
≥40	-0.000	-0.04, p =0.02	-0.000	0.27, p <0.01	0.000	0.15, p <0.01
Race						
White [Reference]						
African American	0.002	1.48, p <0.01	0.001	2.57, p <0.01	0.002	3.38, p <0.01
Hispanic	0.008	6.20, p <0.01	0.005	8.30, p <0.01	0.003	3.84, p <0.01
Others	-0.000	-0.34, p <0.01	-0.003	-5.12, p <0.01	0.005	7.53, p <0.01
Admission Characteristics						
Elective Admission	0.006	2.06, p <0.01	0.005	-10.26, p <0.01	0.006	8.63, p <0.01
Weekend admission	0.001	0.52, p <0.01	0.001	2.52, p <0.01	-0.000	-0.63, p <0.01
Clinical Characteristics						
Previous cesarean	0.033	25.6, p <0.01	0.014	25.54, p <0.01	0.014	18.59, p < 0.01
Gestational hypertension	0.000	0.15, p <0.01	0.001	1.38, p <0.01	-0.001	-0.78, p < 0.01
Multiple gestations	0.003	2.61, p <0.01	0.002	4.14, p <0.01	0.003	4.25, p < 0.01
Pericardial effusion	0.001	1.03, p <0.01	0.00	1.57, p <0.01	0.000	0.47, p < 0.01
Obesity	-.0001	-0.96, p <0.01	-.001	-1.17, p < 0.01	-0.001	-1.74, p < 0.01
Socioeconomic Characteristics						
Household income Percentile						
0-25 [Reference]						
25-50	-0.000	-0.05, p =0.03	0.001	1.64, p <0.01	-0.001	-1.54, p < 0.01
50-75	0.000	0.14, p =0.58	0.000	1.02, p= 0.59	0.000	0.25, p = 40
75-100	0.000	0.14, p =0.31	0.003	0.09, p = 0.02	0.000	0.90, p = 0.30
Insurance						
Public [Reference]						
Private	-0.005	-3.87, p <0.01	-0.003	-4.72, p <0.01	-0.003	-4.40, p < 0.01
Uninsured	-0.000	-0.26, p <0.01	-0.000	-0.03, p <0.01	0.000	0.30, p = 0.14
Social determinants						
Over 300% FPL level	0.009	7.34, p <0.01	0.160	28.70, p <0.01	0.007	9.80, p < 0.01

Bachelor's degree	-0.005	-3.53, p <0.01	0.005	-9.59, p <0.01	-0.001	2.30, p < 0.01
Female Employment	0.005	3.79, p <0.01	0.003	4.66, p <0.01	0.002	2.23, p < 0.01
Hospital characteristics						
Teaching hospital	-0.001	-0.53, p <0.01	0.002	4.66, p <0.01	0.005	-7.29, p < 0.01
Medium bed size	-0.002	-1.63, p = 0.06	0.000	0.45, p <0.01	0.000	0.49, p = 0.795
Markup ratio	0.029	22.4, p < 0.01	0.011	20.10, p < 0.01	0.001	2.05, p=0.02

Table 4. Hospital resource and health outcome differences between cesarean and Vaginal delivery across US States

Outcome	Vaginal delivery	Cesarean delivery	Multivariate Odds ratio (95% CI), P value
Readmission, No (%)			
Wisconsin	420 (0.91)	317 (1.94)	1.33 (1.15-1.41), p < 0.01
Florida	1528 (1.33)	1777 (2.42)	1.47 (1.28-1.65), p < 0.01
New York	1452 (0.98)	1583 (2.12)	1.61 (1.45-1.87), p < 0.01
Unplanned ED visits, No (%)			
Wisconsin	1659 (3.6)	670 (4.1)	1.12 (1.06-1.21), p < 0.01
Florida	4737 (4.16)	3372 (4.64)	1.08 (1.02-1.15), p <0.01
New York	5747 (3.9)	3271 (4.4)	1.07 (1.01-1.13), p =0.02
Hospital cost, median (IQR) $			
Wisconsin	3524 (2649-4619)	6369 (5158-6369)	p < 0.01
Florida	2708 (2054-3625)	4794 (3721-6384)	p < 0.01
New York	3990 (2961-5224)	6203 (4728-8123)	p < 0.01
Length of stay, median (IQR) days			
Wisconsin	2 (2-2)	3 (3-4)	p < 0.01
Florida	2 (2-3)	3 (2-3)	p < 0.01
New York	2 (2-3)	3 (3-4)	p < 0.01