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Abstract: A patient’s medical insurance coverage plays an essential role in determining the post-acute care (PAC) discharge disposition. The prior authorization process postpones the PAC discharge disposition, increases the inpatient length of stay, and affects patient health. Our study implements predictive analytics for the early prediction of the PAC discharge disposition to reduce the deferments caused by prior authorization and in turn minimizes the inpatient length of stay, and inpatient stay expenses. We conducted a group discussion involving 25 patient care facilitators (PCFs) and two registered nurses (RNs) and retrieved 1600 patient data records from the initial nursing assessment and discharge notes to conduct a retrospective analysis of PAC discharge dispositions using predictive analytics. The chi-squared automatic interaction detector (CHAID) algorithm enabled the early prediction of the PAC discharge disposition, accelerated the prior health insurance process, decreased the inpatient length of stay by an average of 22.22%. The model produced an overall accuracy of 84.16% and an area under the receiver operating characteristic (ROC) curve value of 0.81. The early prediction of PAC discharge dispositions can reduce the PAC delay caused by the prior health insurance authorization process and simultaneously minimize the inpatient length of stay and related expenses incurred by the hospital.

ABOUT THE AUTHOR
Sunanda Perumalla is a senior data scientist at the Integris Health, Oklahoma. She graduated from Texas Tech University in 2018. Her research interest encompasses medical informatics and applied machine learning.
Avishek Choudhury is a graduate student at Syracuse University. His research interest includes cognitive human factors, medical informatics, and artificial intelligence.

PUBLIC INTEREST STATEMENT
Post-acute care (PAC) is one of the many healthcare services hindered by prior authorization. Delayed PAC can result in poor care, higher readmission rates, and suboptimal patient outcomes. The inpatient stays of patients discharged to PAC are typically lengthier and more expensive than routine discharges. The stay length and cost are influenced by the complexity of medical conditions and PAC facility placement delays caused by prior health insurance authorization requirements. The Institute for Healthcare Improvement says that hospital-wide patient flow should deliver the right care, in the right place, at the right time. Given the benefits and potential of machine learning in the healthcare domain, in this study we show how a simple model can assist in predicting PAC services required by patients, enable doctors to commence the process of prior authorization in advance and thereby, reduce delays caused due to prior authorization process by 22%.
1. Introduction

1.1. Prior authorization

Almost every diagnostic test or therapeutic intervention ordered by a hospital, except for the most common blood tests and standard radiographs, mandates prior authorization from the patient’s health insurance provider (Malay, 2019). Obtaining prior authorization is cumbersome and often involves several steps that delay the procurement of the information needed to make a proper diagnosis and institute ideal treatment. The delay caused due to the prior authorization process not only deters patient safety but also can affect the doctor-patient relationship. As described by Dr. Neierenberg (see box 1), the burden of prior might invoke a high cognitive workload on clinicians (doctors).

Prior authorization also imposes administrative costs, both on the insurance company and the care providers. Prior authorization forces post-acute care patients and their providers to navigate an additional barrier when seeking access to care—a barrier that is perceived to be time-consuming and nontransparent (Housten et al., 2018). Some studies have reported the negative impacts of delays caused due to the prior authorization process. Delays due to prior authorization have affected care quality in clinical specialties such as pain management (Hartung et al., 2004; Onukwugha et al., 2009) and mental health (Soumerai et al., 2008). Delays due to prior authorization have resulted in increased emergency department visits (Hartung et al., 2004), poor adherence, (Hoppe et al., 2014; Soumerai et al., 2008; Zhang et al., 2009) and increased medical expenses (Onukwugha et al., 2009).

Moreover, prior health authorization issues are concomitant, with 92% of care deferments contributing to patient harm and administrative ineptitudes (American medical association, 2018). According to the American medical association’s survey that assessed a thousand patient care physicians’ experiences, 64% reported delays for prior authorization decisions from insurers of at least one business day, and 30% stated they wait for three to four business days longer (American medical association, 2018). Besides, 8 out of 10 physicians said the hindrances related to prior health insurance authorization were high, and 86% of these physicians believed that burdens associated with prior authorization have increased over the past five years and led to increases in Medicare spending, PAC obligations, and the services provided by insurance companies, including bundled SNF payments (Buntin et al., 2005).

1.2. Post-acute care

Post-acute care (PAC) is one of the many healthcare services hindered by prior authorization. PAC focuses on improving activities of daily living (ADL) through physical and occupational therapy and health education (Dolansky et al., 2010). For example, patients with cardiac discomfort receive PAC tailored to their cardiac events, such as monitoring the cardiac response to therapy, learning self-
management of cardiac symptoms, survival management, and cardiac education. PAC has involved multiple providers administering aid in a disconnected manner and poor communication throughout the health care system (Abrams et al., 2017). When a patient requires PAC services, there is currently little reason given as to why a patient is discharged to a skilled nursing facility (SNF), a home health agency, an acute rehabilitation (AR) facility, or a long-term acute care hospital (Burrill, 2017). The demand for PAC has been increasing with an increase in the geriatric population. According to the US Census Bureau, by 2050, the geriatric population will increase to 88.5 million (Miller et al., 2000; Vincent & Velkoff, 2010). Typically, older adults suffer from multiple ailments and chronic conditions (Aungst & People, 2011). Thus, the geriatric population requires more medical resources and requires lengthy hospital stays and PAC assistance to attain desirable health restitution (McKee & Healy, 2001; Y-S Lee et al., 2012). More than one-third of stroke patients in the United States are discharged to PAC facilities, including AR, SNFs, and long-term care facilities (Tian, 2006). One out of five patients is admitted to PAC after being discharged from the hospital (about 8 million patients annually) (Tian, 2006). On average, 22.8 % of SNF patients end up back in the hospital within 30 days of their discharge (Burke et al., 2016). In 2014, patients suffering from neurological diseases comprised 13% of Medicare cases in AR, up from 5% in 2004 (Commission, 2008). This increase led to a rise in Medicare spending, which grew from 20.3 USD billion in 2001 to 41.3 USD billion in 2014 (Commission, 2008).

Delayed PAC can result in poor care, higher readmission rates, and suboptimal patient outcomes (Burrill, 2017). The inpatient stays of patients discharged to PAC are typically lengthier and more expensive than routine discharges (McKee & Healy, 2001; Y-S Lee et al., 2012). The stay length and cost are influenced by the complexity of medical conditions (LK Chen et al., 2010; Gill et al., 2002; Mahoney & Barthel, 1965) and PAC facility placement delays caused by prior health insurance authorization requirements. The Institute for Healthcare Improvement says that hospital-wide patient flow should deliver the right care, in the right place, at the right time (Lawton & Brody, 1969). PAC discharge dispositions require the meticulous coordination of insurance administrators and patients (Schwendimann et al., 2006). They are also affected by the availability of required settings, the accessibility of the patient, and pecuniary incentives that might not be allied with medical requirements or cost-effectiveness (Garøsen et al., 2007). A whitepaper from the Institute for Healthcare Improvement suggests working with AR and SNF facilities to improve patient flow through advanced planning, coordination, and partnership development (Lawton & Brody, 1969). However, no significant research has been performed to address advanced PAC discharge disposition planning and improved coordination between acute and post-acute services (Yesavage et al., 1982).

1.3. Role of machine learning
In healthcare, machine learning (ML) research has started to have a significant impact on clinicians (e.g., aiding for accurate image interpretation), patients (e.g., assisting processing their data to engage better), and healthcare system (e.g., improving workflow and reducing medical errors) (Bhardwaj et al., 2017). The integration of ML into the healthcare system is changing the dynamics, such as the role of healthcare providers and creating new potentials to improve patient safety (Macrae, 2019), as well as the quality of care (Grossman et al., 2018). It has assisted clinicians in making better diagnoses (Bahl et al., 2018; Guan et al., 2019; Li et al., 2019), improved drug safety (H Chen et al., 2018; Costabal et al., 2019; Ekins et al., 2019), and enhanced patient-care monitoring (Banerjee et al., 2019; Ciervo et al., 2019; Dalal et al., 2019; Jiang et al., 2017; Ronquillo et al., 2018). Machine learning enables computers to utilize labeled (supervised learning) or unlabeled data (unsupervised learning) to identify latent information or make classification about the data without explicit programming (Hashimoto et al., 2018; Jiag et al., 2017). With the increasing amount of data within the healthcare industry, the prevalence of implementing machine learning is gaining momentum (Kong, 2019). Today in healthcare, a large amount of data is available from Electronic Health Records (EHRs), which contains both structured and unstructured data (Bhardwaj et al., 2017), and machine learning can allow computers to learn from EHR data and develop predictions by identifying hidden patterns (Hashimoto et al., 2018; RY Lee et al., 2019).
Given the benefits and potential of ML in the healthcare domain, we hypothesize that ML can also assist in predicting PAC services required by patients and thus enable doctors to commence the process of prior authorization in advance. According to research, PAC, when provided on time, has improved the physical independence and recovery of patients (Buntin et al., 2005). This study proposes an advanced PAC discharge disposition plan and leverages the ML algorithm to address PAC delay caused by prior health insurance authorization.

2. Methodology

This study does not involve patient participation, and no personal patient information has been revealed. All analysis and patient data were conducted on anonymized retrospective data. The group discussion in the study was a part of a routine monthly activity where the analytics team and the care providers meet to discuss systemic problems and develop possible solutions.

The methodology of this study can be broadly categorized into the following sections: (a) group discussion and problem identification, and (b) model selection and assessment.

2.1. Group discussion and problem identification

To study the PAC discharge disposition procedures and determine the bottlenecks responsible for PAC discharge delays and long inpatient stays, we conducted an online group discussion involving 25 patient care facilitators (PCFs) and two registered nurses (RNs). The following three main questions were discussed in this session.

- What criteria do we use to determine whether a patient should go to acute rehabilitation?
- What criteria do we use to determine whether a patient should go to a skilled nursing facility?
- Is there a defined process map that we follow before a doctor signs a patient discharge note? (only to the RNs)

The participants for the group discussion were selected by the senior nurse and senior process improvement engineer. The participants were recruited across three hospitals in Iowa, USA.

To address the bottleneck without changing the clinical workflow and organizational structure, we developed a model to predict the discharge disposition of patients based on patient health data collected during the initial nursing assessment. Predicting the discharge location can enable the hospital to commence the prior authorization process in advance.

2.2. Data collection

We retrospectively retrieved anonymized data records of 1600 patients (from July 2018 through August 2018) from discharge and preoperative assessment notes. The raw anonymized data were used for all analyses and contained 629 variables not limited to Hester Davis Fall Risk score, Braden Scale Score, chest pain, history of fracture, history of alcohol abuse, hypertension, history of stroke, and sepsis. Our analysis included only patients discharged to AR or SNF, and missing data and deceased patient data were excluded. For practical reasons, we categorized the data into the following 14 categories: (a) patient personal information, (b) home setup, (c) PT/OT reasons, (d) Impairment group, (e) history of present illness, (f) medical history, (g) surgical history, (h) family history, (i) allergies, (j) current medication, (k) lab results, (l) vitals, (m) tolerance, and (n) functional deficit.

2.3. Model selection

We used SPSS Modeler and implemented the following five machine learning algorithms: (a) linear discriminant analysis (LDA), (b) the chi-squared automatic interaction detector (CHAID), (c) a random tree (RT) method (d) a linear support vector machine (LSVM), and (e) a classification and regression tree (CART). The model that provided the best fit was chosen based on the following performance measures: (a) overall accuracy and (b) area under the ROC curve (AUC-ROC). Discussing each algorithm is beyond the scope of this study. Figure 1 illustrates the ML framework adopted in this study.
3. Results

3.1. Group discussion outcomes

All participating PCFs (n = 25) and RNs (n = 2) agreed that the PAC discharge type was primarily driven by medical insurance coverage and physical therapy (PT) and occupational therapy (OT) evaluations of a patient. During PT and OT evaluations, care providers used Braden Scale Scores and Hester Davis Fall Risk Scores to identify the high-risk patient. They also noted the importance of health conditions, such as a stroke, hip fracture, or spinal cord injury, in mandating AR or SNF service for a patient. Additionally, to qualify for PAC, the patient must tolerate three hours of therapy and be covered by medical insurance.
Figure 2. The existing PAC discharge disposition process (for a traditional practice without predictive modeling). In this practice, the hospital requests insurance after all clinical procedures are completed. The patient and the hospital wait for two days on average for the insurance coverage confirmation. This two-day waiting time adds no value to the healthcare services of the patient but increases the inpatient length of stay, hinders patient health, and delays PAC.

Figure 2 shows an approximate protocol that PCFs, RNs, and doctors typically follow to manage PAC discharges at our target hospitals. The figure was developed based on the group discussion and included only the crucial steps involved in actual practice relevant to this study.

After a discharge decision is made and confirmed by both the post-acute care facilitatory (PCF) and the doctor, the hospital initiates the prior health insurance authorization process; it takes two days on average (Beaton, 2018) for the insurance company to confirm whether a patient is insured for AR or SNF, thus postponing the discharge by two days. This process was identified as the bottleneck region responsible for PAC discharge disposition delays and long inpatient stays.

3.2. Data description
Table 1 shows the average Braden scale score, Hester-Davis fall risk score, and the average age of patients per discharge dispositions. Table 2 shows the descriptive statistics of the data set.

The Braden Scale was developed by Barbara Braden and Nancy Bergstrom in 1988. It is a required assessment method for identifying a patient with a risk of pressure ulcers (Ding et al., 2019). It involves six different risk factors: sensory perception, skin moisture, activity, mobility, nutrition, friction, and shear (Griswold et al., 2017) and the total scores range from 6–23. A Braden scale score of 9 or less indicates severe patient risk; a score between 10 and 12 indicates high risk; the moderate risk is denoted by score 13–14; a score between 15 and 18 indicates mild risk.

Hester Davis Scale for fall risk assessment is a nine-factor scale with scores ranging from 0 to 77. A score of 7–10 indicates a low risk to fall, 11–14 indicates a moderate risk to fall, and a score greater than 15 shows high fall risk (Hester & Davis, 2013). Hester Davis Scale involves nine factors: age, date of last known fall, mobility, medications, mental status, toileting needs, volume electrolyte status, communication or sensory function, and behavior. Each factor is a scale item with response categories consisting of increasing levels of risk. The total score obtained from the different indicators (factors) is used to determine if the patient is at risk to fall, and if so, a level of risk is assigned based on the abovementioned scores.

3.3. Normality test
Figure 3A illustrates the data (mean and 95% confidence interval). All data points were also tested for normality using the Shapiro-Wilk test. Figure 3B shows the QQ-plot for patient age and risk assessment scales. The patient age in the AR facility failed to pass the normality test (shaded in red). We compared the risk assessment scores and patient age between SNF and AR. As shown in Table 3, the non-normal data were compared using the Mann-Whitney test. Data that were
normally distributed were compared using the two-tailed t-test shows the statistical differences between the two PAC facilities. We observed a significant difference in patient age (p-value <0.00) and fall risk (p-value <0.00) between the two facilities.

### 3.4. Comparative analysis of predictive models

The CHAID algorithm, with the highest overall accuracy of 84.16% and a ROC value of 0.81, was selected as the best fit model. Table 4 shows the accuracy and the area under the ROC curve of the top five tested models.

Age, Braden scale score, and Hester Davis fall risk score were observed to be the strongest predictors of PAC discharge disposition.

| Discharge Disposition                                                                 | Gender | Age | Braden Scale Score | Hester Davis Fall Risk Score |
|-------------------------------------------------------------------------------------|--------|-----|---------------------|-----------------------------|
| Another Health Care Institution Not Defined                                        | Male   | 2 (0.13%) | 64 | 20 | 7 |
|                                                                                     | Female | Missing | 64 | 10 |
| Federal Hospital                                                                   | 4 (0.26%) | 68 | 13 | 12 |
| Psychiatric Hospital                                                              | 5 (0.33%) | 49 | 15 | 9 |
| Rehab Facility                                                                     | 24 (1.58%) | 14 (0.92%) | 66 | 17 | 11 |
| Short-term General Hospital for Inpatient Care                                     | 4 (0.26%) | 2 (0.13%) | 59 | 17 | 9 |
| Skilled Nursing Facility                                                            | 76 (5.01%) | 114 (7.52%) | 76 | 16 | 12 |
| Swing Bed                                                                          | 1 (0.06%) | 1 (0.06%) | 92 | 15 | 15 |
| Intermediate Care Facility                                                         | 12 (0.79%) | 17 (1.12%) | 73 | 15 | 14 |
| Home Health Care Service                                                           | 75 (4.95%) | 45 (2.97%) | 65 | 18 | 9 |
| Long-term Care                                                                     | Missing | 3 (0.19%) | 79 | 15 | 12 |
| Dead                                                                                | 13 (0.85%) | 8 (0.52%) | N/A | N/A | N/A |
| Home or Self Care                                                                  | 499(32.93%) | 552 (36.43%) | 57 | 20 | 7 |
| Hospice                                                                            | 7 (0.46%) | 5 (0.33%) | 72 | 18 | 14 |
| Hospice Medical Facility                                                           | 11 (0.72%) | 6 (0.39%) | 79 | 16 | 13 |
| Left Against Medical Advice                                                        | 10 (0.66%) | 3 (0.19%) | 51 | 19 | 7 |
| Court/Law Enforcement                                                              | 1 (0.06%) | Missing | 40 | 15 | 26 |

Table 1. Discharge disposition, patient demographics, and average risk assessment scores
3.5. Proposed process map with CHAID predictive model

Figure 4 shows the process map after implementing CHAID. The CHAID model identified eligible AR and SNF patients during the initial nursing assessment, thereby allowing the hospital to initiate the prior health insurance authorization process on the first day of an inpatient stay (rather than at the end of the inpatient stay). Early commencement of prior authorization reduced the average length of an inpatient stay from $x$ days to $x-2$ days (22.22% decrease).

The proposed model and workflow do not interfere with clinical processes or replace physician decisions. PT/OT evaluation, initial and continued nursing assessment, and all other essential clinical activities can be processed while the medical insurance company confirms the patient’s insurance coverage, and the patient will not have to wait an extra two days to obtain health care.

Table 2. Descriptive statistics

| Predictor               | Age (years) | Braden Scale Score | Hester-Davis Fall Risk Score |
|-------------------------|-------------|--------------------|------------------------------|
| Min                     | 16          | 1                  | 3                            |
| Max                     | 97          | 26                 | 23                           |
| Range                   | 81          | 25                 | 20                           |
| Mean                    | 71.90       | 12.44              | 15.52                        |
| Mean Std. Error         | 1.37        | 0.42               | 0.37                         |
| Std. Deviation          | 15.56       | 4.83               | 4.18                         |
| Variance                | 242.16      | 23.39              | 17.52                        |
| Skewness                | −1.30       | 0.15               | −1.01                        |
| Skewness Std. Error     | 0.21        | 0.21               | 0.21                         |
| Kurtosis                | 2.51        | −0.16              | 1.21                         |
| Kurtosis Std. Error     | 0.42        | 0.42               | 0.42                         |

Table 3. Comparing skilled nursing facility and acute rehabilitation

| Factors                   | Statistics                          | Comparing | Skilled Nursing Facility | Acute Rehabilitation Facility |
|---------------------------|-------------------------------------|-----------|--------------------------|-----------------------------|
|                           | Non-parametric Mann-Whitney test (alpha 0.05) |           |                          |                             |
| Age                       | Sum of ranks                        |           | 1002                     | 951.5                       |
|                           | Hodges-Lehmann                       |           | −12                      |                             |
|                           | Mann-Whitney U                       |           | 248.5                    |                             |
|                           | P-value                              |           | 0.0018                   |                             |
|                           | Parametric two-tailed t-test (Welch’s t-test) (alpha 0.05) |           |                          |                             |
| Braden Scale Score        | Welch-corrected t                    |           | 0.59                     |                             |
|                           | R squared                            |           | 0.00                     |                             |
|                           | P-value                              |           | 0.55                     |                             |
| Hester Davis Fall Risk    | Welch-corrected t                    |           | 2.71                     |                             |
| Score                    | R squared                            |           | 0.12                     |                             |
|                           | P-value                              |           | 0.0089                   |                             |
Table 4. Comparative analysis of predictive models

| Sl. No. | Model | Overall Testing Accuracy | Area Under the ROC |
|---------|-------|--------------------------|--------------------|
| 1       | LDA   | 83.33                    | 0.79               |
| 2       | CHAID | 84.16                    | **0.81**           |
| 3       | RT    | 72.50                    | 0.68               |
| 4       | LSVM  | 76.66                    | 0.70               |
| 5       | CART  | 80.00                    | 0.51               |
Figure 4. Process map showing the advantage of implementing the CHAID model. The CHAID model removes the extra two days of waiting time. Prior health insurance authorization can be performed parallel with the other clinical procedures conducted during an inpatient stay, thereby reducing inpatient length of stay.

insurance authorization after the doctor recommends the discharge location. The model is designed to encourage advanced PAC discharge disposition planning by proactively gauging medical insurance coverage in parallel with the inpatient stay. The new process map ensures the recursive training of the CHAID model, which enhances its reliability and robustness over time and provides a support system for all medical experts.

4. Discussion and conclusion
This is the first study that integrates a prediction model into an existing clinical workflow and proposes a process map that can help clinicians determine patients’ PAC needs based on their initial nursing assessment. Moreover, the patient identified as a PAC candidate without insurance can be provided with alternate care recommendations. Predicting PAC discharge disposition does not ensure timely prior authorization. The prior authorization process, mainly a product by commercial insurance payers, adds significant delay in a treatment process, which is directly harmful in many health care scenarios. Our study does not address the delays in the prior authorization process, but it allows the providers to commence prior authorization in advance.

Additionally, national projections suggest that hospitals may be overcrowded with patients affected with coronavirus (COVID-19) in the coming months. Appropriately, much attention has addressed the acute challenges in caring for this surge of critically ill patients. However, not much has been done to manage PAC services and related prior authorization. Many patients with COVID-19 will require post-acute care to recover from their infection (Grabowski & Joynt Maddox, 2020). Our model and workflow may assist in identifying patient’s PAC requirements and thus help in managing PAC services. This will also facilitate faster patient transfer and help in vacating up hospital beds for severely ill patients.

5. Summary
5.1. What is known
- Healthcare providers and patients are expected to experience long delays before their prior health insurance authorization applications are sanctioned.
- Seventy-eight percent of providers stated that long prior health insurance authorization processes are associated with patients stopping their treatments.
- Lengthy inpatient waiting time contributes to increased healthcare expenses and poor health outcomes.
5.2. Our contributions

- This is the first study that implements advanced planning for PAC discharge types and consecutively minimizes the inpatient length of stay.

- The CHAID algorithm implemented in this study yielded an accuracy of 84.16%.

- The study uses real data in the analyses.

- The PAC discharge time is reduced by 22.22%.

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Author details

Avishek Choudhury1
E-mail: achoudh@syr.edu
ORCID ID: http://orcid.org/0000-0002-5342-0709

Sunanda Perumalla2

1 Applied Data Science, Syracuse University, Syracuse, USA.
2 Senior Data Scientist, Integris Health, Oklahoma.

Notes on contributions

AC conceived and designed the study, participated in data collection, analysis, and interpretation, drafted and revised the manuscript, and approved the final version for submission. SP participated in data analysis, and data interpretation, drafted and revised the manuscript, and approved the final version for submission.

Competing interest statement

The authors declare they have no conflict of interest in this study.

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