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Identifying Patterns of Medical Intervention in Acute Respiratory Failure: A Retrospective Observational Study

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IMPORTANCE: Characterizing medical interventions delivered to ICU patients over time and their relationship to outcomes can help set expectations and inform decisions made by patients, clinicians, and health systems.

OBJECTIVES: To determine whether distinct and clinically relevant pathways of medical intervention can be identified among adult ICU patients with acute respiratory failure.

DESIGN, SETTING, AND PARTICIPANTS: Retrospective observational study using all-payer administrative claims data from 2012 to 2014. Patients were identified from the Healthcare Cost and Utilization Project State Inpatient Databases from Maryland, Massachusetts, Nevada, and Washington.

MAIN OUTCOMES AND MEASURES: Patterns of cumulative medical intervention delivery, over time, using temporal k-means clustering of interventions delivered up to hospital days 0, 5, 10, 20, and up to discharge.

RESULTS: A total of 12,175 admissions were identified and divided into training (75%; $n = 9{,}130$) and validation sets (25%; $n = 3{,}045$). Without applying a priori classification and using only medical interventions to cluster, we identified three distinct pathways of intervention accounting for 93.5% of training set admissions. We found 45.9% of admissions followed a "cardiac" intervention pathway (e.g., cardiac catheterization, cardioversion); 36.7% followed a "general" pathway (e.g., diagnostic interventions); and 17.4% followed a "prolonged" pathway (e.g., tracheostomy, gastrostomy). Prolonged pathway admissions had longer median hospital length of stay (13 d; interquartile range [IQR], 7.5–18.5 d) compared with cardiac (5; IQR, 2.5–7.5) and general (5; IQR, 3–7). In-hospital death occurred in 24.6% of prolonged pathway admissions compared with 17.9% of cardiac and 6.9% of general. Findings were confirmed in the validation set.

CONCLUSIONS AND RELEVANCE: Most ICU admissions for acute respiratory failure follow one of three clinically relevant pathways of medical intervention which are associated with hospitalization outcomes. This study helps define the longitudinal nature of critical care delivery, which can inform efforts to predict patient outcomes, communicate with patients and their families, and organize critical care resources.

KEYWORDS: critical illness; intensive care; mechanical ventilation; respiratory failure

Acute respiratory failure is one of the most common organ dysfunctions among hospitalized adults in the United States and is one of the leading reasons for admission to an ICU (1–3). Mortality for patients admitted to the ICU with acute respiratory failure is high, with approximately one third of patients dying in the hospital (2, 4–6). Mechanical ventilation is the primary medical intervention available to support patients with this syndrome and has been a primary focus of epidemiologic and health services research to

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KEY POINTS

Question: What are the typical patterns of medical interventions delivered to patients with acute respiratory failure in the ICU?

Findings: In this retrospective observational study using 12,175 ICU admissions from all-payer administrative claims data from 2012 to 2014, we identified three distinct, clinically relevant pathways of medical intervention that were associated with hospital outcomes.

Meaning: These findings contribute to a better understanding of the longitudinal course of ICU care delivery for patients with acute respiratory failure, which is characterized by multiple medical interventions.

understand and improve ICU care delivery for patients with acute respiratory failure (2–4, 7, 8).

However, patients with acute respiratory failure typically receive multiple medical interventions over the longitudinal course of ICU care (9). These interventions are used to diagnose and treat the underlying cause of respiratory failure, support additional and later-onset organ dysfunctions (10–12), and facilitate care such as the administration of nutrition and medications. Although the multiple-intervention nature of critical illness is readily apparent, little is known about the patterns of these interventions and their relationship to patient outcomes. Given that the characteristics of acute critical illness at ICU admission (severity, diagnoses) become increasingly less predictive of outcomes as an ICU stay progresses over time (13), a better understanding of the patterns of intervention during an ICU stay may reveal important determinants of patient outcomes. Furthermore, an improved understanding of how acute respiratory failure typically evolves over time can help set clearer expectations for critically ill patients and their families who are facing an unfamiliar challenge (14) and inform the organization of critical care and hospital resources within health systems.

To address this knowledge gap, we sought to identify and characterize patterns of medical interventions delivered to patients admitted to the ICU with a primary diagnosis of acute respiratory failure. We hypothesized that the interventions delivered to patients with acute respiratory distress can be categorized into typical patterns that unfold over time as distinct "pathways" of care.

METHODS

Data Source and Patient Selection

We used data from the Healthcare Cost and Utilization Project (HCUP) State Inpatient Databases (SIDs) from Maryland, Massachusetts, Nevada, and Washington, from 2012 to 2014 (15). We selected these four SIDs because they each included an ICU admission status variable and represented different geographic regions and different state-level patterns of end-of-life healthcare delivery (16). The study was reviewed by the Northwestern University Institutional Review Board (IRB) and determined not to be human subjects research (IRB number: STU00209269). The analyses were conducted between January 2019 and October of 2021. This report follows the Strengthening the Reporting of Observational Studies in Epidemiology guidelines for reporting observational studies (17).

We included ICU admissions of adult patients (age ≥ 18), defined by an ICU indicator in the HCUP SID database. The indicator is derived from Uniform Billing (UB-04) revenue codes, *International Classification of Diseases*, 9th Revision, Clinical Modification (ICD-9-CM) procedure codes, and the HCUP Clinical Classification Software. We further limited inclusion to patients who were admitted directly to the ICU without any preceding general hospital admission and to patients with a primary ICD-9 diagnosis of acute respiratory failure. A flow diagram with complete exclusion criteria and numbers of admissions meeting each criterion is provided in **eFigure 1** (http://links.lww.com/CCX/B258).

We defined medical interventions delivered to patients based on ICD-9-CM procedure codes provided in the HCUP SID, which also includes the day of hospitalization on which the procedure was performed. We included all coded medical interventions for each admission, from hospital presentation to discharge. Hospital discharge disposition in the HCUP SID is derived from the patient status data element on the UB-04 claim form. We categorized available discharge dispositions into six groups: home, inpatient rehabilitation facility, skilled nursing facility, long-term acute care hospital, hospice (home or inpatient), or dead at time of discharge (i.e., in-hospital mortality).

Clustering Analysis

We used a k-means algorithm to uncover pathways of medical intervention delivered to subgroups of patients without imposing any a priori hypotheses (**Fig. 1**). We clustered patient admissions solely according to medical interventions delivered. Within the dataset, we identified 228 unique interventions across all cohort admissions (e.g., intubation, echocardiogram, bronchoscopy, thoracentesis). We then represented the set of these interventions with a binary vector of dimension 228. A value of 1 at dimension *i* indicates that the patient received the intervention within the analytic timeframe and a value of 0 indicates that they did not. Note that for any given patient, this vector is sparse, because each admission only included a subset of possible interventions. We then clustered the vectors according to a k-means procedure, where k represents the number of possible clusters. To determine the value of k, we used the Bayesian information criteria (18), with the optimal k being determined to be 3. To identify pathways of intervention, we conducted the clustering procedure for serial time periods. Each clustering analysis started with admission day 0 and included the cumulative interventions delivered up to day *t* of the admission, where *t* = 1, 5, 10, 20 days, and at discharge. To ensure comparability of these five serial time periods, we removed patients whose first intervention was only recorded after day 2. All analyses were conducted using R (Version 4.0.2, R Foundation for Statistical Computing, Vienna, Austria) and Python's scikit-learn library (Python Software Foundation, Wilmington, DE).

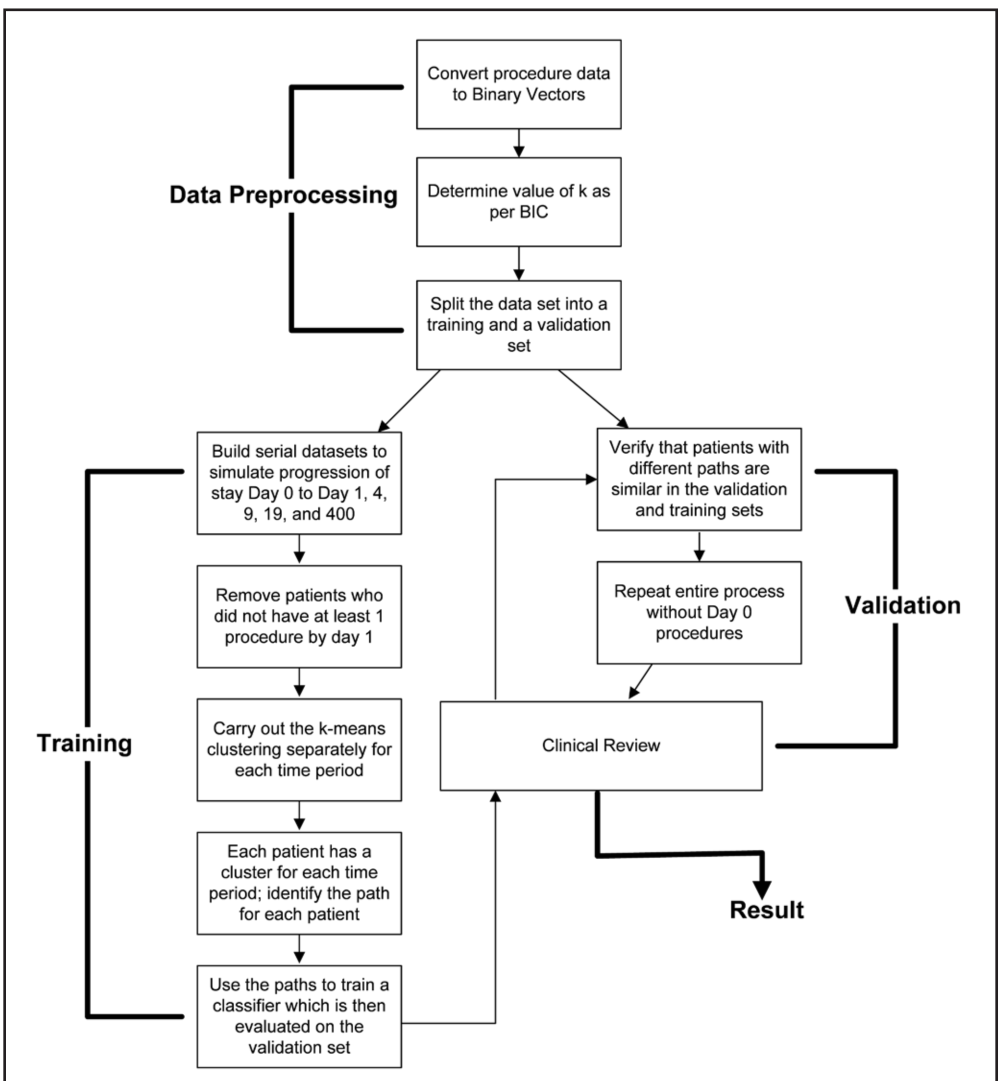

Figure 1. Clustering analysis flowchart. Flowchart of clustering analysis used to identify distinct and clinically relevant longitudinal pathways of medical intervention delivered to patients with acute respiratory failure. BIC = Bayesian information criterion.

Validation Analysis

For validation, we split the dataset into training (75%) and validation (25%) sets. The training set was used to estimate the clusters at each period and the validation set was used to verify the reproducibility of the results. We clustered the training set into three clusters for each period, as described above. We then fit an optimal tree classification model to predict the cluster labels using the procedure vectors for the training set (19). This tree model was then used to assign cluster labels to the validation set. We further verified the validity of our process by comparing the results predicted by the optimal clustering tree model to intervention pathways obtained by implementing the clustering process as on the training set. For more than 95% of included admissions, the pathway predicted by the optimal tree classification model was the same as that obtained by the clustering process. Training set results are presented in the article and validation set results are in **eTables 1** and **2** (http://links.lww.com/CCX/B258).

Identification of Distinct Intervention Pathways

To evaluate whether the clusters had distinguishing features, we excluded interventions that were shared among all three clusters at any time period. The physician investigators (J.M.K., J.L.H.) then examined the most frequent medical interventions in each cluster for clinically relevant patterns. We evaluated whether similar patterns of interventions were present across periods and evaluated the proportion of ICU admissions within the same cluster at every time. To determine whether pathway membership was associated with patient characteristics (age, sex, race, comorbid conditions) and outcomes (total number of medical interventions, discharge disposition, length of stay), we used chi-square and Wilcoxon rank-sum tests.

Sensitivity Analysis

We found that 52.2% of all medical interventions were listed as occurring on the first day of admission (day 0). It is possible that this accurately reflects the nature of critical care, where many interventions are delivered at initial presentation to the ICU or it may reflect a bias in the dataset, where interventions are incorrectly coded as occurring on day 0. Thus, to test whether the pathway results were entirely dependent on day 0 interventions, we repeated the serial clustering procedure after removing day 0 interventions.

RESULTS

Identification of Medical Intervention Pathways

The total cohort included 12,175 adult ICU admissions for acute respiratory failure, divided into a training set (75%; n = 9,130 encounters) and a validation set (25%; n = 3,045 encounters). Given the cohort was divided into three clusters (k = 3) and five serial time periods, each patient encounter had a potential of $3^5 = 243$ different cluster assignments. However, our analysis revealed that 93.5% of patient admissions were classified into the same intervention cluster over all five time periods (**Fig. 2**), leading to the identification of three predominant pathways of medical intervention. The remaining 6.5% of admissions were classified into multiple different clusters or different patterns of clusters with no identifiable pathway(s) within this group.

Characteristics of Medical Intervention Pathways

The most common pathway, labeled post hoc as "cardiac," accounted for 45.9% of admissions. The most frequent interventions in this pathway are related to cardiac diagnoses and treatments (e.g., echocardiogram, coronary arteriography, cardiac catheterization, cardioversion). A second distinct pathway, labeled "general," accounted for 36.7% of admissions and was distinguished by its diagnostic interventions (e.g., thoracentesis, chest CT scan). A third pathway, labeled "prolonged," accounted for 17.4% of admissions and included medical interventions associated with the facilitation of prolonged life-sustaining intervention (e.g., mechanical ventilation longer than 96 hr, tracheostomy, and gastrostomy). **Table 1** shows the five most frequent interventions in each cluster in each period, after removing interventions shared across all three clusters. The sensitivity analysis produced similar results, after removing admissions with interventions only coded as delivered on day 0. **Table 2** shows patient characteristics and outcomes for the training set and for each of the three intervention pathways. Fewer female patients followed the "prolonged" pathway (48.1%) compared with the general pathway (56.8%; $p < 0.0001$).

Outcomes of Medical Intervention Pathways

Patient outcomes differed according to the three distinct pathways. Admissions following the prolonged pathway included a higher number of medical interventions (median $n = 5$) compared with the cardiac pathway ($n = 3$; $p < 0.0001$) and general pathway ($n = 1$; $p < 0.0001$). Median hospital length of stay was 13 days for patients in the prolonged pathway

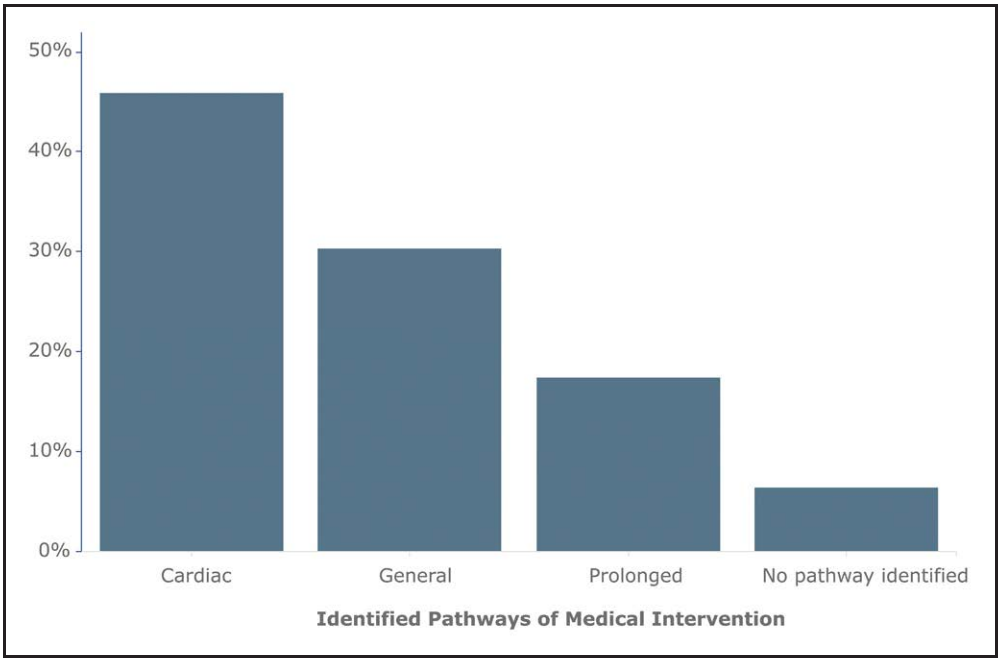

Figure 2. Percentage of cohort in each identified pathway of medical intervention. Distribution of ICU admissions for acute respiratory failure into distinct medical intervention pathways. The three predominant pathways accounted for 93.5% of all patients and were given the descriptive labels of "cardiac" critical illness, "general" critical illness, and "prolonged" critical illness. The descriptive labels were assigned after clustering, according to the hallmark interventions defining the cluster.

compared with 5 days for patients in both the cardiac and general paths ($p < 0.0001$ for both comparisons). Patient admissions in the prolonged pathway were also more likely to result in death (24.6%), discharge to hospice (4%), or discharge to a post-acute care facility (13.04%) compared with patient admissions in the cardiac (17.9%, 2.9%, 2.7%) and general (6.9%, 4%, 3%) pathways. The sensitivity analysis produced similar results (**eTable 3**, http://links.lww.com/CCX/B258), with patient characteristics and hospitalization outcomes after excluding patients with medical interventions only coded on day 0.

DISCUSSION

In this study, we identified three distinct pathways of medical intervention delivery among patients with acute respiratory failure admitted to ICUs in four states in the United States. We conducted an unsupervised, temporal clustering analysis using only medical interventions to derive these pathways, without applying any a priori hypotheses to the data. These pathways have construct validity because the interventions that distinguish them align with recognizable clinical subgroups, including cardiac conditions and the syndrome commonly referred to as chronic or persistent critical illness (7, 13, 20). The three pathways of medical intervention delivery also differ according to patients' total number of interventions, length of hospitalization, in-hospital mortality, and location of discharge.

For researchers seeking to understand the determinants of and predict patient outcomes in acute respiratory failure, these findings highlight the potential for incorporating patterns of medical intervention delivery into modeling approaches. Traditional approaches have primarily focused on static models using patient physiology, primarily using data available at presentation in the ICU (21–28). More recent work has demonstrated the value of using machine learning methods to incorporate temporal trends of patients' physiologic data into prediction of long-term outcomes (28, 29). Our findings add to this work by suggesting that, in addition to physiology, trends in medical intervention delivery should be considered. While there is obvious cross-correlation between patients' physiology and medical interventions delivered, our findings align with prior work suggesting that patterns of intervention delivery have an important association with patient outcomes. For example, another observational study demonstrated that patterns of vasopressor use (e.g., late-onset) in critically ill patients are associated with mortality (12). Plausible mechanisms of these relationships may include downstream complications of the intervention itself (30) or the prognostic significance of requiring multiple or additional interventions to maintain "stable" physiology. With advances in machine learning techniques, accounting for this cross-correlation between physiology and delivered interventions is now more feasible (31) and can be considered in future work.

TABLE 1.
Most Frequently Coded Medical Interventions Delivered to Adults With Acute Respiratory Failure Admitted to the ICU[a]

Up to Hospital Day 1	Up to Hospital Day 5	Up to Hospital Day 10	Up to Hospital Day 20	Entire Hospitalization
Cardiac pathway interventions				
MV < 96 hr	MV < 96 hr	Intubation	Intubation	Intubation
Intubation	Intubation	**Cardiac catheterization**	**Cardioversion**	**Cardiac catheterization**
Nasogastric tube	**Cardioversion**	Nasogastric tube	**Cardiac catheterization**	Nasogastric tube
Bronchoscopy	Nasogastric tube	**Echocardiogram**	Nasogastric tube	**Echocardiogram**
Cardiac catheterization	**Cardiac catheterization**	Indwelling urinary catheter	**Echocardiogram**	Bronchoscopy
General pathway interventions				
Thoracentesis	Vaccinations	Vaccinations	MV > 96 hr	MV > 96 hr
Vaccinations	MV < 96 hr	Echocardiogram	Vaccinations	Vaccinations
MV < 96 hr	Cardiac catheterization	Indwelling urinary catheter	Echocardiogram	Echocardiogram
Arterial blood gas	**CT scan chest**	Cardiac catheterization	Indwelling urinary catheter	Indwelling urinary catheter
CT scan chest	**Arterial blood gas**	OR procedures on blood vessels[b]	Cardiac catheterization	Cardiac catheterization
Prolonged pathway interventions				
MV > 96 hr[c]	**MV > 96 hr**	**MV > 96 hr**	**MV > 96 hr**	**MV > 96 hr**
Intubation	Intubation	Intubation	Intubation	Intubation
Nasogastric tube	Cardioversion	**Tracheostomy**	**Tracheostomy**	**Tracheostomy**
Non-OR cardiovascular procedures[d]	Nasogastric tube	Non-OR respiratory procedures	**Gastrostomy**	**Gastrostomy**
Bronchoscopy	Non-OR respiratory procedures[e]	Electroencephalogram	Bronchoscopy	Bronchoscopy
Shared interventions among all three pathways				
MV unknown time	MV unknown time	MV < 96 hr	MV < 96 hr	MV < 96 hr
Venous catheterization	Venous catheterization	Venous catheterization	Venous catheterization	Venous catheterization
Other therapies (includes infusion of vasopressor and other common ICU medications)[f]	Blood transfusion	MV unknown time	MV unknown time	MV unknown time
Blood transfusion	Enteral and parenteral nutrition	Blood transfusion	Blood transfusion	Blood transfusion
Enteral and parenteral nutrition	Other therapies (includes infusion of vasopressor and other common ICU medications)[f]	Enteral and parenteral nutrition	Enteral and parenteral nutrition	Enteral and parenteral nutrition

(*Continued*)

TABLE 1. (*Continued*)

Most Frequently Coded Medical Interventions Delivered to Adults With Acute Respiratory Failure Admitted to the ICU[a]

Up to Hospital Day 1	Up to Hospital Day 5	Up to Hospital Day 10	Up to Hospital Day 20	Entire Hospitalization
Hemodialysis	Hemodialysis	Other therapies (includes infusion of vasopressor and other common ICU medications)[f]	Hemodialysis	Hemodialysis
Arterial catheterization	Endoscopic biopsy of bronchus	Hemodialysis	Other therapies (includes infusion of vasopressor and other common ICU medications)[f]	Other therapies (includes infusion of vasopressor and other common ICU medications)[f]
Cardioversion	Arterial catheterization	Endoscopic biopsy of bronchus	Endoscopic biopsy of bronchus	Endoscopic biopsy of bronchus
Endoscopic biopsy of bronchus	Coronary arteriography	Arterial catheterization	Arterial catheterization	Arterial catheterization
Indwelling urinary catheter	Thoracentesis	Cardioversion	Coronary arteriography	Coronary arteriography

MV = mechanical ventilation, OR = operating room.

[a]The five most frequent interventions at each time period within each cluster are displayed (not shared among all three clusters). Bold text indicates hallmark interventions that defined the labeling of each trajectory. Individual *International Classification of Diseases*, 9th Revision (ICD-9) procedure codes were classified according to the Healthcare Cost and Utilization Project Clinical Classification Software for ICD-9 Clinical Modification, using the lowest (i.e., most specific) level of classification.

[b]Includes: OR procedures on 1, 2, 3, 4+ blood vessels or a vessel bifurcation, insertion of vascular stents, noncoronary intraoperative fluorescence vascular angiography, incisions into specific vessels (e.g., aorta, abdominal vein or artery), endarterectomies, vessel resection and anastomosis or replacement, varicose vein stripping and ligation, vessel excision or occlusion or suturing, vascular procedure revisions, aneurysm and fistula repairs or clipping, insertion of nondrug eluting peripheral vessel stents, operations on carotid body, sinus, and other vascular bodies, and other vessel operations or hemorrhage control.

[c]Interventions in the dataset are coded at the end of hospitalization, which accounts for the label of MV > 96 on hospital day 1. In real-time, this intervention/pathway would be distinguishable from the general intervention pathway at 96 hr (4 d).

[d]Including: supersaturated oxygen therapy, peripheral and coronary artery stenting, therapeutic injection into heart or pericardium, venous cutdown, venous catheterization for renal dialysis, "total body" perfusion and other perfusion procedures, and nonoperative removal of heart assist system.

[e]Including: Other lavage of bronchus and trachea, tracheal/laryngeal stent procedures, tracheostomy "toilette," replacement or removal of tracheostomy tube, removal of thoracotomy or pleural drainage tube, removal of mediastinal drain, injection of therapeutic substance into trachea, tracheoesophageal fistulization, endoscopic excision or destruction of lesion or tissue of bronchus or of lung, destruction of phrenic nerve, artificial pneumothorax or pneumoperitoneum for collapse of lung, endoscopic insertion or removal of bronchial valves, devices, or substances, bronchial dilation, suture of chest wall laceration, thoracostomy closure, injection into thoracic cavity, and removal of sutures or other devices from thorax.

[f]Including: Infusion of vasopressor, injection or infusion of immunoglobulin, antidote, insulin, electrolytes, anticoagulant, platelet inhibitor, anti-infective, steroid, hormone, tranquilizer, infusion of drotrecogin alfa (activated), administration of inhaled nitric oxide, injection/infusion of nesiritide, pressurized treatment of venous bypass graft with pharmaceutical substance, infusion of immunosuppressive antibody therapy, transplant from live related donor, transplant from live nonrelated donor, transplant from cadaveric donor, intraoperative neurophysiologic monitoring, injection or infusion of glucarpidase, infusion of four-factor prothrombin complex concentrate, intracranial pressure or oxygen monitoring, brain temperature monitoring, robotic-assisted procedures, other puncture of an artery, other puncture of a vein, radiosurgery, nonmechanical resuscitation, hyperbaric oxygen, decompression chamber, irrigation of a vascular catheter, wound irrigation, replacement of wound catheter, packing, or drain, removal of sutures, drains, or other devices, injection of Rh factor immune globulin, immunization for allergy or autoimmune disease, iontophoresis, therapeutic plasmapheresis/leukopheresis/erythropheresis/plateletpheresis/photopheresis, aquapheresis, hypothermia, ultraviolet light therapy, isolation, hyperthermia for treatment of cancer, noninvasive placement of bone growth stimulator, acupuncture, milk extraction, and other miscellaneous procedures.

TABLE 2.
Patient Characteristics and Hospitalization Outcomes Organized by the Three Emergent Intervention Pathways

Characteristic	Full Training Cohort, $n = 9,130$	Cardiac Intervention Pathway, $n = 4,190$	General Intervention Pathway, $n = 2,765$	Prolonged Intervention Pathway, $n = 1,587$	Pairwise Pathway Comparisons, p (Cardiac to General Pathway Comparisons, General to Prolonged Pathway Comparisons, Cardiac to Prolonged Pathway Comparisons)
Patient characteristics					
Age, yr, mean (SE)	65 (0.15)	63.9 (0.25)	66.7 (0.28)	63.4 (0.38)	< 0.001, < 0.001, NS
Sex, %					
Female	51.1	49.5	56.8	48.1	< 0.001, < 0.001, NS
Male	48.9	50.5	43.2	51.9	
Race, %					
Asian or Pacific Islander	3.6	3.8	3.2	4.0	
Black	8.6	8.9	8.6	8.9	
Hispanic	6.1	6.5	5.3	6.7	
Native American	0.8	1.0	0.6	1.0	
Other[a]	1.3	1.0	0.7	2.4	
White	79.6	78.8	81.5	76.9	
Number of comorbid conditions, median (IQR)	4.0 (3.0–5.0)	4.0 (2.5–5.5)	4.0 (3.0–5.0)	4.0 (3.0–5.0)	< 0.001, <0.05, < 0.001
Most frequent secondary diagnoses (% of admissions with diagnosis)	Obstructive chronic bronchitis (25.1), pneumonia (24.8), congestive heart failure (24.6)	Congestive heart failure (24.3), fluid and electrolyte disorders (22.3), pneumonia (22.1)	Obstructive chronic bronchitis (40.0), congestive heart failure (28.1), pneumonia (23.9)	Pneumonia (28.7), acute renal failure (26.7), aspiration pneumonitis (23.7)	

(*Continued*)

TABLE 2. (*Continued*)

Patient Characteristics and Hospitalization Outcomes Organized by the Three Emergent Intervention Pathways

Characteristic	Full Training Cohort, $n = 9,130$	Cardiac Intervention Pathway, $n = 4,190$	General Intervention Pathway, $n = 2,765$	Prolonged Intervention Pathway, $n = 1,587$	Pairwise Pathway Comparisons, p (Cardiac to General Pathway Comparisons, General to Prolonged Pathway Comparisons, Cardiac to Prolonged Pathway Comparisons)
Hospitalization characteristics					
Total number of medical interventions received, median (IQR)	3.0 (1.5–4.5)	3.0 (2.0–4.0)	1.0 (0.5–1.5)	5.0 (3.0–7.0)	< 0.001, < 0.001, < 0.001
Length of stay, d, median (IQR)	7.0 (3.5–10.5)	5.0 (2.5–7.5)	5.0 (3.0–7.0)	13.0 (7.5–18.5)	< 0.05, < 0.001, < 0.001
Discharge disposition, %					< 0.001, < 0.001, < 0.001
Home	47.7	53.8	59.9	26.7	
Inpatient rehabilitation	4.1	3.7	1.8	7.8	
Skilled nursing facility	22.1	19.0	24.4	23.8	
Long-term acute care hospital	5.4	2.7	3.0	13.0	
Hospice	3.7	2.9	4.0	4.0	
Died	17.0	17.9	6.9	24.6	

IQR = interquartile range, NS = no statistical difference.

[a]Other, as designated in the Healthcare Cost Utilization Project State Inpatient Databases, represents other races not included in listed categories and missing or otherwise unavailable data.

For critically ill patients with acute respiratory failure and their families, these findings may help inform expectations about an ICU stay. For example, our findings suggest that patients who will go on to experience a prolonged pathway of ICU care may be identifiable as early as 96 hours into the ICU stay, given that the ICD-9 code for mechanical ventilation greater than 96 hours was the key hallmark intervention distinguishing this pathway from others. Families of critically ill patients report a desire for information about expected medical interventions (14), and a more tangible description of typical intervention patterns may help patients and their families prepare for and engage throughout the course of a critical illness. We and others have recognized the psychologic effects of sunk costs and "clinical momentum" that build in the ICU setting, influencing clinicians, patients, and families (9, 32). These hidden influences can be permissive of additional medical intervention while delaying the process of aligning care with patients' goals and priorities (33). By making the longitudinal pathways of ICU care delivery more transparent, this work can inform efforts to incorporate individual patients' goals and priorities more explicitly into all ICU care delivery.

For ICU clinicians and health systems, these findings may inform ongoing efforts to improve planning for ICU occupancy and care resources. These intervention pathways could be used to forecast medium-term resource needs in the ICU and within the hospital, based on a current census of ICU patients. In addition to forecasting ICU beds, procedural space, and equipment, intervention pathways could help forecast staffing needs over a period of days based on the nature and the number of expected interventions for the current ICU occupants. This approach expands upon existing scores like the Therapeutic Intervention Scoring System, currently used to estimate nurse staffing for a single shift based on patients' intervention needs (34). The need for new approaches to forecast staffing is high given a widespread shortage of nurses (35), with an ongoing increase of ICU clinicians leaving the field due to burnout (36).

This study has several limitations. First, the study sample represents ICU admissions from only four U.S. states, which limits the generalizability of the findings to other states and countries. The dataset also represents hospital admissions and ICU care delivered before the onset of the COVID-19 pandemic, and future work should focus on whether the patterns of care identified in this study have changed after this highly influential event. This analysis was also limited to patients directly admitted to an ICU, without any prior stay on a general hospital unit. While this approach focuses on pathways of medical intervention delivered in ICUs, future study is needed to understand the longitudinal course of care for patients admitted to general hospital units, including those who may be subsequently transferred to the ICU. Third, the analysis was limited to medical interventions recorded in an administrative dataset with ICD-9 codes, which is unlikely to be comprehensive and can contain undetected, systematic errors because ICD-9 codes are typically applied at the end of a hospitalization. Nevertheless, our findings are robust to sensitivity analyses. Fourth, the timing of intervention delivery within the dataset is indicated by day of hospitalization and we only included admissions with an intervention delivered within the first 2 days of hospitalization. A more detailed analysis of the time of intervention delivery (e.g., from electronic health records) in future work may help identify the earliest timepoint that pathway membership can be established and uncover previously underrecognized pathways of care (e.g., beyond cardiac, general, and prolonged).

CONCLUSIONS

In this retrospective study of administrative data, we found that most ICU admissions for adults with acute respiratory failure follow one of three distinct pathways of medical intervention delivery and that these pathways are associated with patient outcomes.

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All authors contributed to the conception and design, data analysis, and interpretation of data were involved in drafting the article *or revising it critically for important intellectual content and gave approval for the final version before submission.*

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