2014

Abstract 1007: Development of Tele-ICU Multidimensional Severity Adjusted PIRO Sepsis Model

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Citation
Critical Care Medicine. 2014 42(12 Supp 1): A1602

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Development of Tele-ICU Multidimensional Severity Adjusted PIRO Sepsis Model

Predisposition, Insult/Injury, Response, Organ Dysfunction /Outcomes (PIRO)

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Introduction: The purpose of this study was to determine the effect of pre-existing health and acute illness characteristics on sepsis responses and outcomes in Intensive Care Unit (ICU) patients by leveraging data acquisition technology in large complex data bases, specifically inputs from Tele-ICU technology.

Hypothesis: Contributions of person level and pre-existing health and acute illness characteristics will estimate risk of sepsis severity, mortality, and acutely acquired organ dysfunction (AAOD).

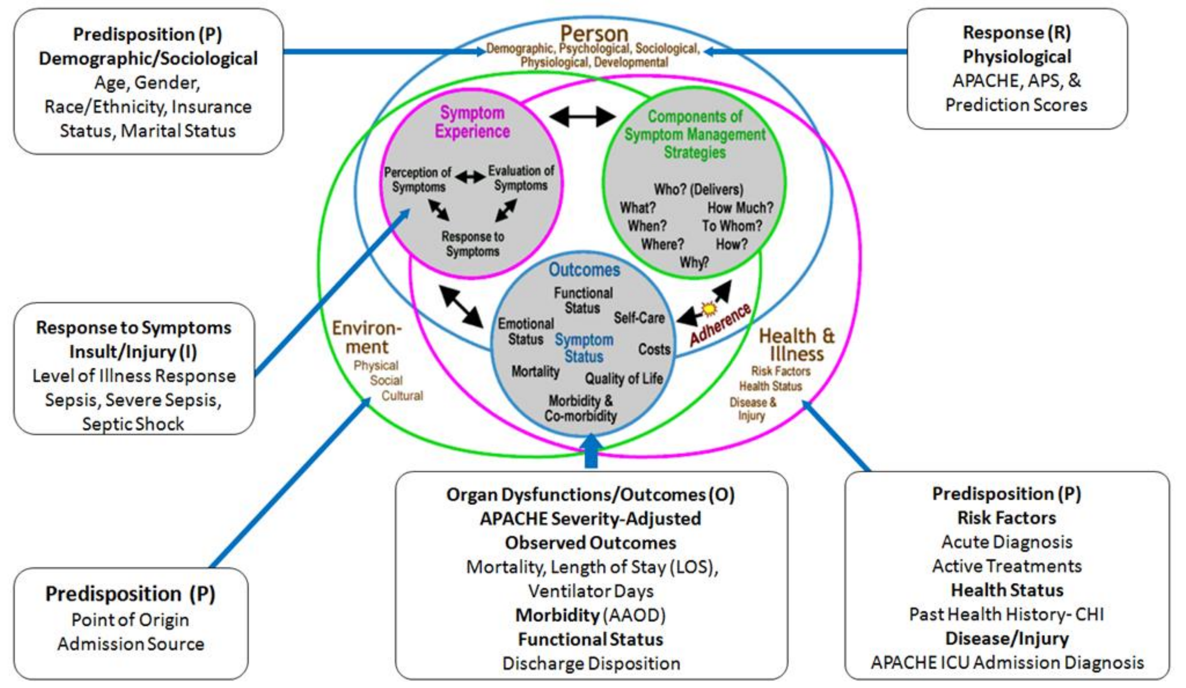
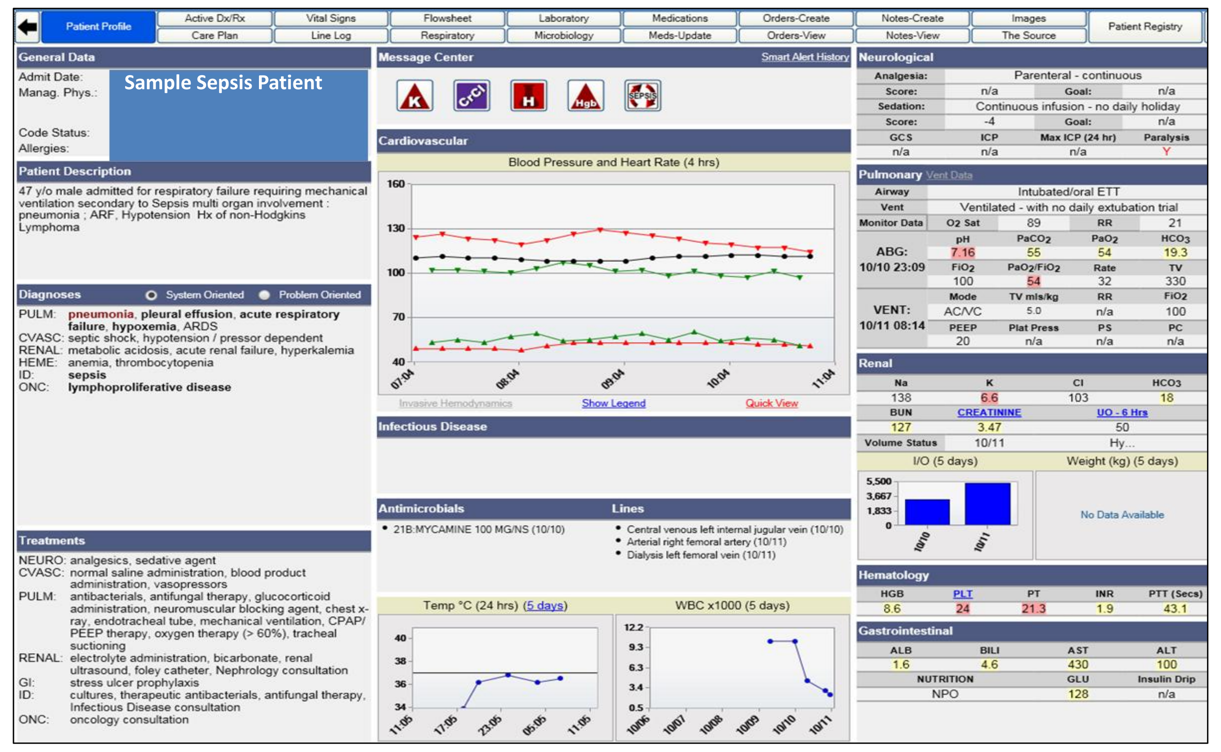


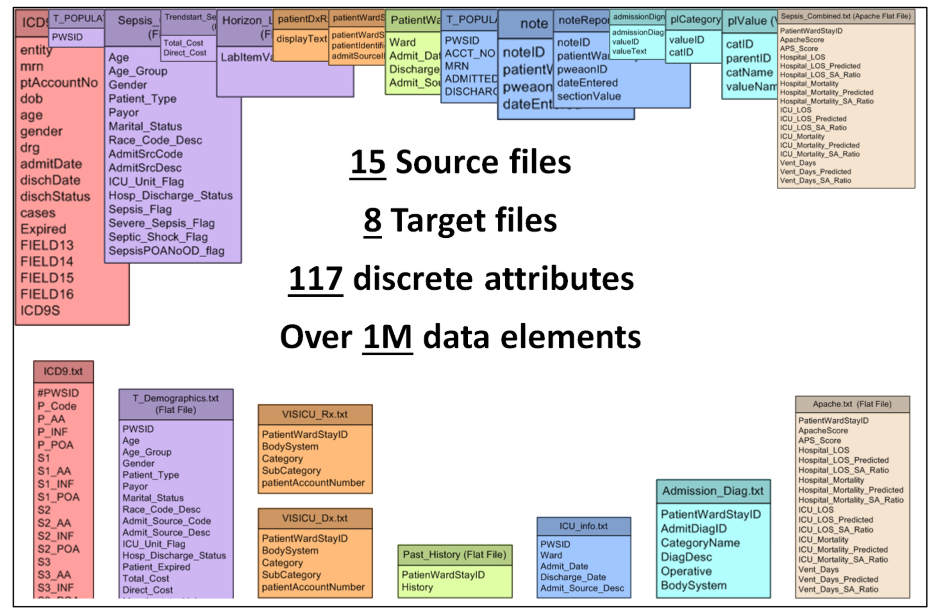
Figure 1. Armaignac (2013) Adaptation of Symptom Management Theoretical Model to provide a framework to define, organize, and visualize interrelationships among sepsis Predisposition, Insult/Injury, Response, Organ Dysfunctions/Outcomes (*PIRO*) concepts

Development of Robust Multivariate Sepsis Related Data Base

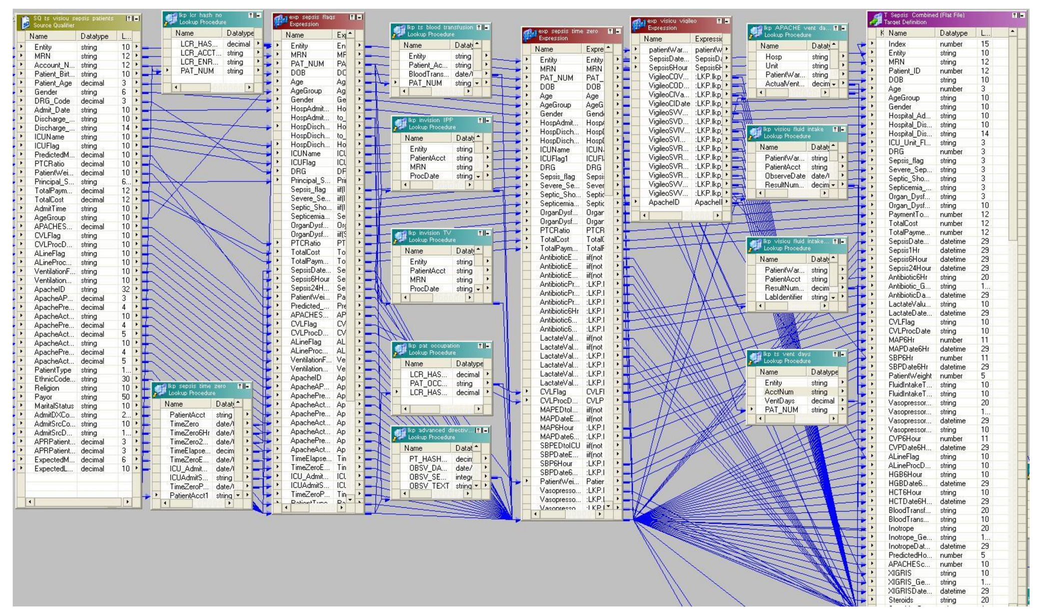


Challenge: The conduct of high value applied epidemiologic research is contingent upon data sources. Baptist Health South Florida, a large healthcare organization, is in the midst of transformation of extremely high volume of data to best possible use. There was no market available product to seamlessly transform OLTP data to OLAP, so we organized internally to achieve this goal.

Solution: Data Transformation Process. We utilized *Informatica* Data Warehouse Software and advanced methods of technologically mining clinical data in large complex data bases. Discrete data items were captured and compiled through a number of interfaces, multiple data platforms, electronic medical record (EMR), and ICU documentation systems.



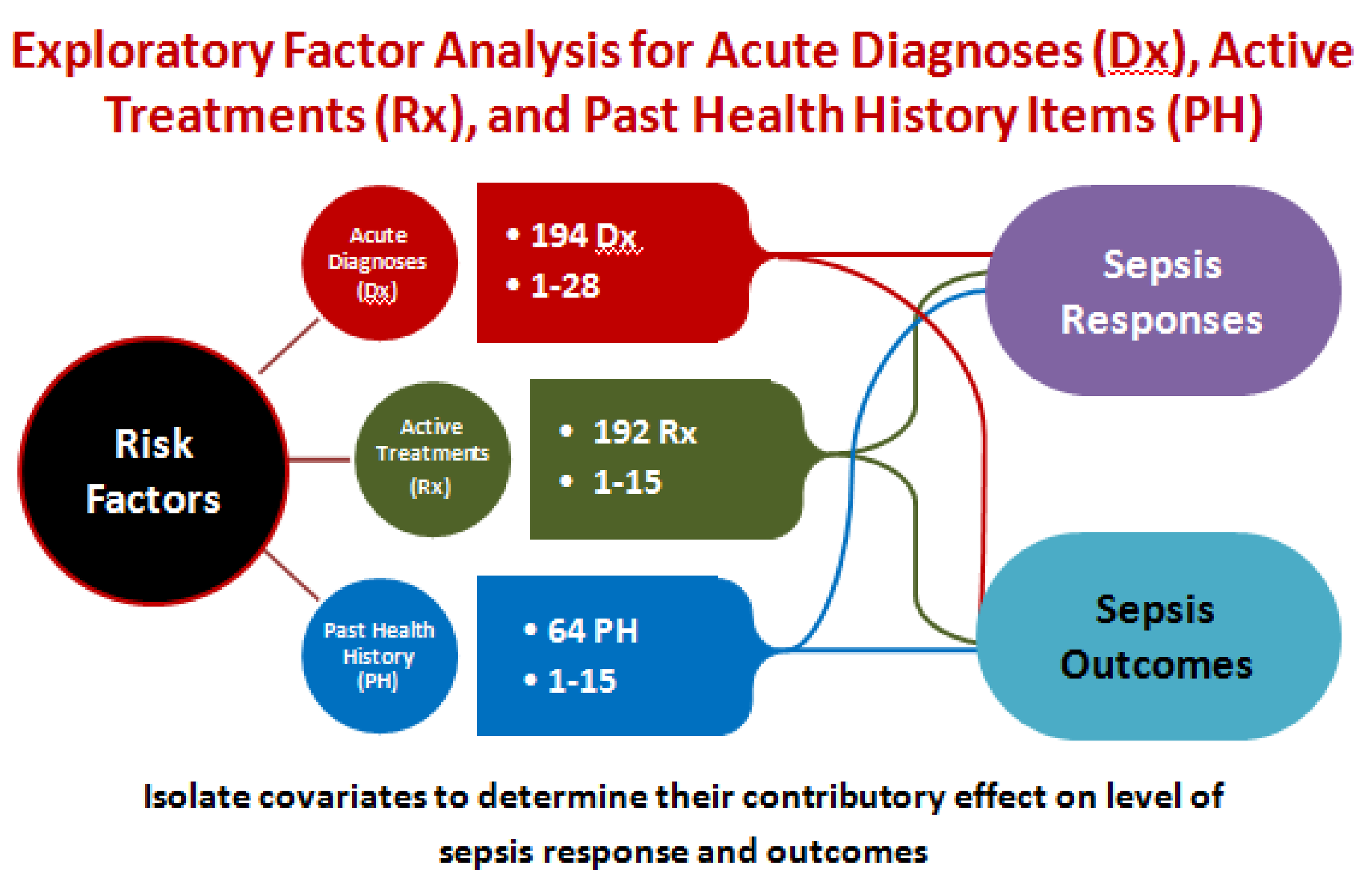
The data structure design was completed with the following steps: (a) determine primary keys; (b) assign tables; (c) design research database; (d) verify procedure to ascertain correct data variables and/or data parameters; (e) validate procedure to ensure the sourced information was what the research study required; (f) back-end server data transformed to flat files; and (g) mapped files into statistical software for analysis.



We acquired essential attributes required for study. Utility of the database was tested by creation of several sophisticated prediction models.

Materials and Methods: Observational cohort obtained at 6 hospitals from 2008 to 2013 (n = 10,232; 5,643 sepsis, 2,321 severe sepsis, 2,268 septic shock). Sampling method was validated with a subset of patients against a retrospective chart review (validity coefficient 0.88, 95% CI 0.71; 0.96) and prospective clinician identified (0.86, 95% CI 0.69; 0.94) blinded over same period.

Factor Analysis: to identify the effect of Acute Diagnoses (Dx), Active Treatments (Rx), Past Health (PH) and APACHE IV ICU Admission Diagnosis on quality and predictability of PIRO model through the development of a complex Tele-ICU physiological and severity adjusted multidimensional database.



Results: Age, gender, race, insurance and marital status, APACHE IV severity adjusted risk scores and hospital and ICU admit source were considered as predictors in models. Overall mortality 19%, Sepsis 10% (severity adjusted ratio 0.59), Severe Sepsis 20% (0.84) and Septic Shock 40% (1.17). APACHE scores were significant predictors in all models; average APACHE score 68.6; APS 53.9 that was higher than average ICU population (53.8; 40.9).

Table 294

Outcomes for Hospital LOS and Hospital Mortality, ICU LOS and ICU Mortality, and Ventilator Days Ratios between Level of Sepsis

Variable	*n*	Obs./ Pred.	Mean Ratio	SD	Min	Max
Sepsis						
Hospital LOS Ratio	5613	1.01	1.06	1.00	0.03	27.73
Hospital Mortality Ratio	**5594**	**0.59**	**0.52**	**2.66**	**0.00**	**100.00**
ICU LOS Ratio	5589	0.91	1.02	1.70	0.03	85.00
ICU Mortality Ratio	**5487**	**0.41**	**0.29**	**2.35**	**0.00**	**58.82**
Ventilator Days Ratio	1493	1.27	1.16	1.32	0.00	10.39
Severe Sepsis						
Hospital LOS Ratio	2306	1.18	1.31	1.52	0.01	38.46
Hospital Mortality Ratio	**2304**	**0.84**	**1.00**	**3.50**	**0.00**	**71.43**
ICU LOS Ratio	2298	1.12	1.28	2.07	0.02	64.50
ICU Mortality Ratio	**2281**	**0.56**	**0.63**	**3.90**	**0.00**	**100.00**
Ventilator Days Ratio	910	1.57	1.37	1.69	0.03	16.35
Septic Shock						
Hospital LOS Ratio	2247	1.09	1.13	1.15	0.01	16.67
Hospital Mortality Ratio	**2248**	**1.17**	**1.80**	**6.35**	**0.00**	**200.00**
ICU LOS Ratio	2238	1.15	1.20	1.43	0.02	16.75
ICU Mortality Ratio	**2235**	**0.91**	**1.73**	**12.33**	**0.00**	**500.00**
Ventilator Days Ratio	913	1.76	1.50	1.62	0.02	14.08

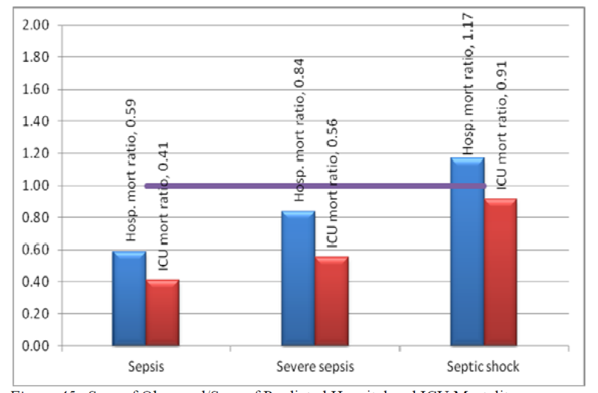


Figure 45. Sum of Observed/Sum of Predicted Hospital and ICU Mortality

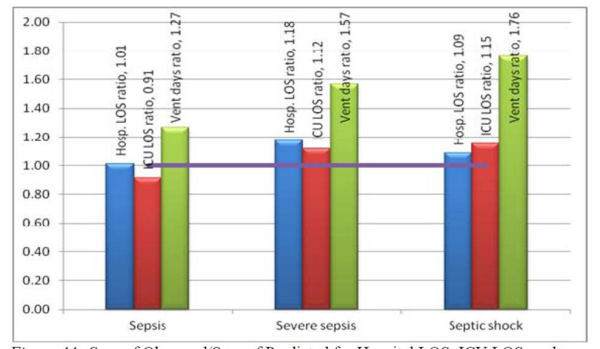


Figure 44. Sum of Observed/Sum of Predicted for Hospital LOS, ICU LOS, and Ventilator Days APACHE

Results: Hispanics higher risk sepsis severity (OR 1.16 *p* <.000). Although, endemic population was predominantly Hispanic 55.6% (white and black Hispanics), Hispanics have not been reported as the most vulnerable race.

Significant Effects of Person Characteristics on Level of Sepsis Response (n = 10, 232)

IV	Person Characteristics	Level of Sepsis DV OR	z	$p>\|z\|$	[95% CI]	
Demographic						
Gender	Male	1.17	3.86	0.000	1.08	1.28
Sociological						
Race/Ethnicity	Hispanic	1.16	3.68	0.000	1.07	1.25
Insurance	Self-pay	0.65	-2.36	0.019	0.46	0.93
	Charity	0.74	-2.41	0.016	0.59	0.94
Marital	Widowed	0.85	-2.72	0.007	0.76	0.95
Physiological	APS	1.03	35.05	0.000	1.03	1.03
Environmental						
ICU Admit	Floor	1.19	3.88	0.000	1.09	1.31
	Operating Room	1.52	5.67	0.000	1.32	1.77

Although age was significantly associated with mortality (*p* =.001), it was not included multivariate models, contrary to sepsis literature; perhaps the difference in this study was due to more in-depth information yielded stronger predictors or age is included in APACHE scores.

Significant Effects of Person Characteristics on Sepsis Outcomes (n = 10, 232)

IV	Person Characteristics	Sepsis Outcomes DV OR	z	$p>\|z\|$	[95% CI]	
		Hospital Mortality				
Demographic	Male Gender	1.19	3.14	0.002	1.06	1.33
Sociological						
Insurance	Self-pay	1.63	2.25	0.025	1.06	2.50
Physiological	APACHE Score	1.03	33.77	0.000	1.03	1.04
Environmental						
Hospital Source	Other Hospital	1.71	2.74	0.006	1.16	2.52
ICU Source	OR	0.71	-2.48	0.013	0.55	0.93
	Recovery	0.51	-3.40	0.001	0.35	0.75
	Floor	1.48	6.35	0.000	1.31	1.68
		ICU Mortality				
Demographic						
Sociological						
Insurance	Medicare/HMO	1.22	2.18	0.029	1.02	1.46
	Self-pay	2.18	2.93	0.003	1.29	3.69
	HMO/PPO/Other	1.57	3.57	0.000	1.22	2.02
	Medicaid/HMO	1.88	3.66	0.000	1.34	2.65
Physiological	APACHE Score	1.04	30.08	0.000	1.03	1.04
Environmental						
		AAOD				
Demographic	Male Gender	1.18	3.71	0.000	1.08	1.29
Sociological						
Physiological	APS	1.01	15.49	0.000	1.01	1.01
Environmental						
ICU Source	Other Hospital	1.70	2.76	0.006	1.16	2.4
	Recovery	2.26	7.98	0.000	1.85	2.76
	SDU	2.35	4.06	0.000	1.55	3.55
	Floor	3.19	22.81	0.000	2.89	3.53
	OR	4.65	18.28	0.000	3.94	5.49

Conclusions: Complexity of big healthcare data provides solid basis to illuminate less frequently studied variables to identify disease sub-types using partitional and hierarchical clustering methods to heuristically uncover apriori differences and create PIRO sepsis risk models.

Lessons Learned: Building a team is of utmost importance. Researcher and field specialist must collaborate closely with IT including engineers, database, and data warehouse professionals. Biostatisticians and Telehealth Data Analyst /Architect are vital members of the team.

To achieve future goals, we plan to continue to develop:
Data mining methods to handle high dimensionality and large data volumes to advance novel predictors from mathematical models and computational intelligence.