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Conference & Exhibition | March 5–9, 2018

Las Vegas | Venetian – Palazzo – Sands Expo Center

Predictive Analytics and the Impact on Nursing Care Delivery

Session 2, March 5, 2018

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KenSci

EvergreenHealth

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Conflict of Interest

Whende M. Carroll, MSN, RN-BC
Master of Science in Nursing, Nursing Informatics

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Have no real or apparent conflicts of interest to report.

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Agenda

- **Predictive Analytics:**
  - Defined
  - The Nurse's Role
  - Driving Value
- **Predictive Analytics: Impact on an Organization**
  - Demonstrate the use of predictive analytics in clinical, educational, and administrative nursing roles
  - Show the impact to the organization each application can have
- **Predictive Analytics: Key Takeaways**

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Learning Objectives

- Define predictive analytics and outline nurses' role
- Discuss the impact that predictive analytics can have on an organization
- Explore how nurses can use predictive analytics to drive value

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Source: http://www.psychics.com/blog/a-brief-history-of-the-crystal-ball/

Predictive Analytics: Defined

- **Mathematical computations** that analyze **historical data** from multiple sources to **predict future events**
- A **machine approach** to refine those data, **using knowledge** to **extract hidden value** from **newly discovered patterns**
- **Dynamically** informs **data-driven decision-making** to know **what will happen, when and what to do about it**

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Predictive Analytics: Defined

How do we make decisions in healthcare?

- **Yesterday and Today** > Traditional Tactics
  - Uninformed – No data
  - Guessing – Some data (maybe)
  - Descriptive – Data-driven dashboards
- **Today and Tomorrow** > Emerging Models
  - *Predictive* - Adding a machine model to structure data to forecast
  - *Prescriptive* - Taking a recommended action based on predictions

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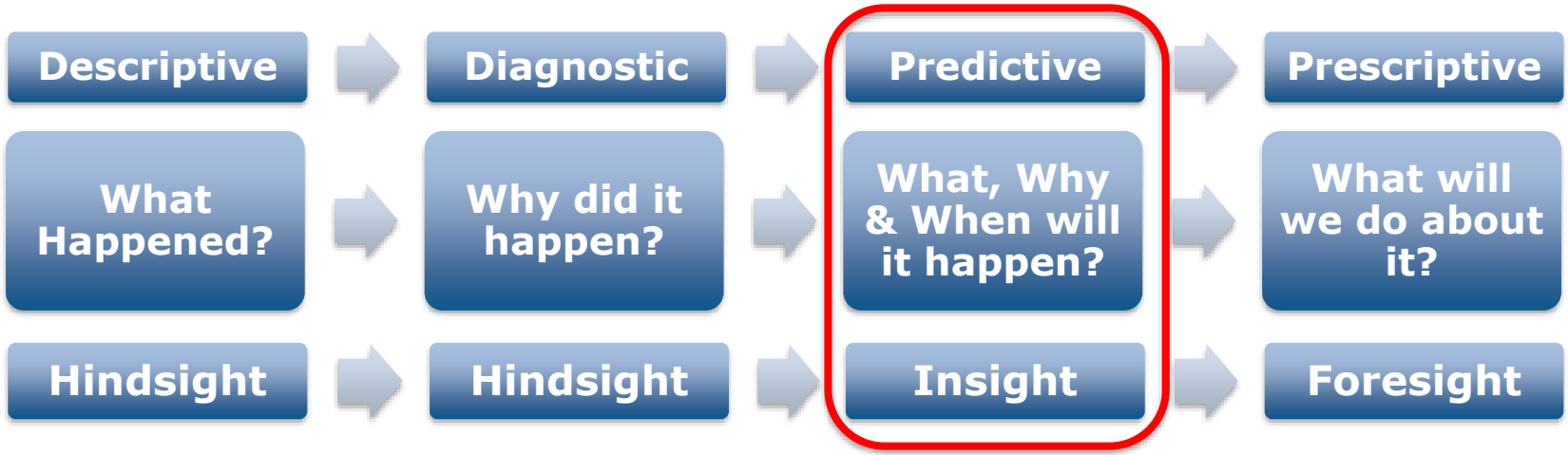
Predictive Analytics: Defined

The Data Healthcare Analytics & Value Spectrum



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Source: Adapted from Gartner Inc., 10/2016

Predictive Analytics: Defined

Types of Predictive Analytics

- Recency, Frequency, Monetary (RFM) Analysis
- Time Series Analysis
- Social Network Survival Analysis
- **Machine Learning =**
  Computer algorithms that improve automatically through experience

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Predictive Analytics: Defined

The Process of Machine Learning

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Predictive Analytics: Nurses' Role

Artificial Intelligence is Altering Healthcare, but Not with "Magic"

Artificial intelligence holds many promises for healthcare providers, but it's unlikely to replace the need for highly-trained clinical minds.

Source: HealthIT Analytics, 11/27/17

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Predictive Analytics: Nurses' Role

- **Nursing Process** - expedites practice
- **Critical Thinking** - augments reasoning
- **Organized Thinking** - enhances structure
- **Clinical Decision Support** - assists capabilities

- **Individualizes Precision Care**
  - The Right Nurse → The Right Patient → The Right Care → The Right Time

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Predictive Analytics: Nurses' Role

- Early Diagnosis of Disease States: **Sepsis**
- Manage Disease Progression: **Congestive Heart Failure**
- Impede Patient Deterioration: **Rapid Response**
- Improve Patient Flow: **Care Planning**
- Decrease Length of Stay/Readmissions: **Care Coordination**
- Match Staffing to Patient Demand: **Efficiency**

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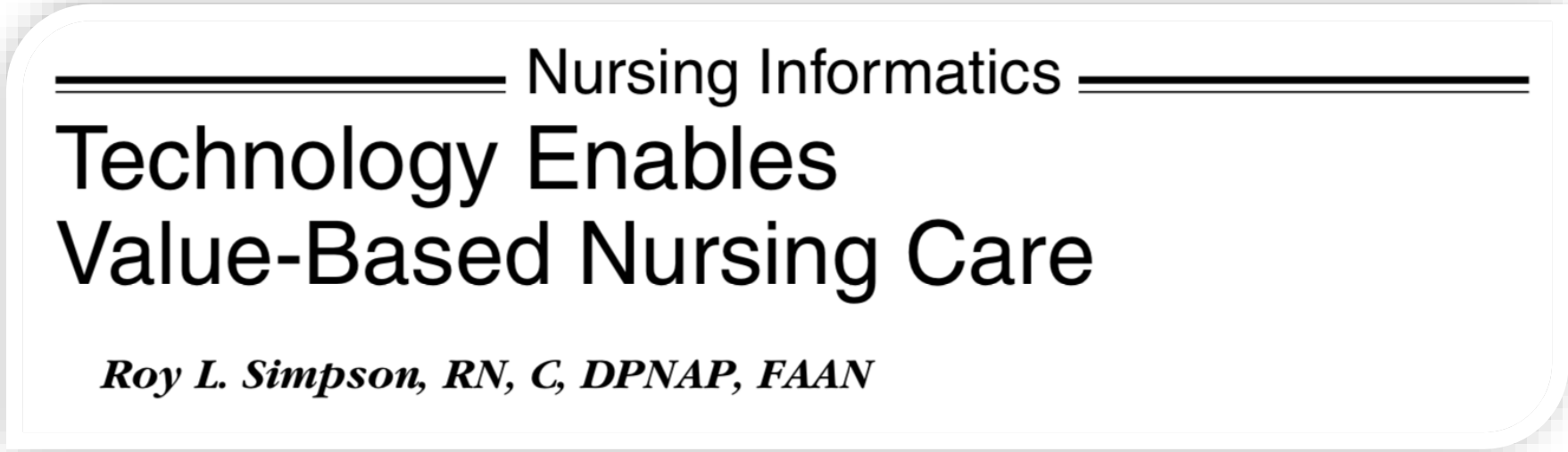
Predictive Analytics: Nurses Driving Value


Nursing Informatics

Technology Enables Value-Based Nursing Care

Roy L. Simpson, RN, C, DPNAP, FAAN

Source: *Nurs Admin Q, 2012,* Vol. 36, No. 1, pp. 85–87

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Predictive Analytics: Nurses Driving Value

How Nurses Add Value to Healthcare = <u>The Quadruple Aim</u>

- **Managing Populations** → Improves quality care and health outcomes
- **Controlling Costs** → Decreases low-value tasks, waste and inefficiencies
- **Improving Patient Satisfaction** → Allows more beneficial time with patients
- **Improve Nurses' Satisfaction** → Transforms the nursing workforce

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Predictive Analytics: Nurses Driving Value

"Improves nursing care practice through better, data-driven decision making at the point of care to deliver safe, quality, individualized, efficient care for populations, decrease costs, and enhance the experience of both patients and nurses"

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Clinical Applications

- **Predicator of deteriorating patients**
  - Modified Early Warning System (MEWS)
  - Maternal Early Warning Trigger (MEWT)
  - Emergency Severity Index (ESI) Scoring

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MEWS Scoring Parameters

	3	2	1	0	1	2	3
Pulse Rate (bpm)		< 40	40-50	51-100	101-110	111-129	>130
Respiratory Rate		<9		9-14	15-20	21-29	>/= 30
Temperature		<35.1	35.1-36	36.1-38	38.1-38.5	>38.5	
Systolic BP	<71	71-80	81-100	101-199		>/=200	
O2Sat	<84	84-87	88-92	93-100			

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Modified Early Warning System (MEWS)

MEWS ↓	HR	Systolic BP	RR	O_2 Sat	Temp	UOP	Print
5	104	112	18	82	36.5	-	Rapid
4	121	96	17	96	36.6	250	Rapid
4	111	138	26	95	36.7	300	Rapid
4	72	144	21	99	34.3	-	Rapid
4	107	152	39	100	37.2	-	Rapid
3	112	137	16	94	36.6	-	Rapid
3	60	124	20	100	34.3	-	Rapid
3	106	110	20	92	37.2	100	Rapid
3	102	118	22	98	36.8	-	Rapid
3	70	92	20	98	35.8	-	Rapid
3	108	99	16	97	37.4	150	Rapid
3	102	126	20	88	37	-	Rapid
3	122	146	16	96	36.7	-	Rapid
3	116	103	18	98	36.4	-	Rapid
2	94	97	18	99	36.5	-	Rapid
2	108	101	16	100	36.4	-	Rapid

Heart Rate is 104 = 1
Respiratory Rate is 18 = 1
O2 Sat is 82 = 3

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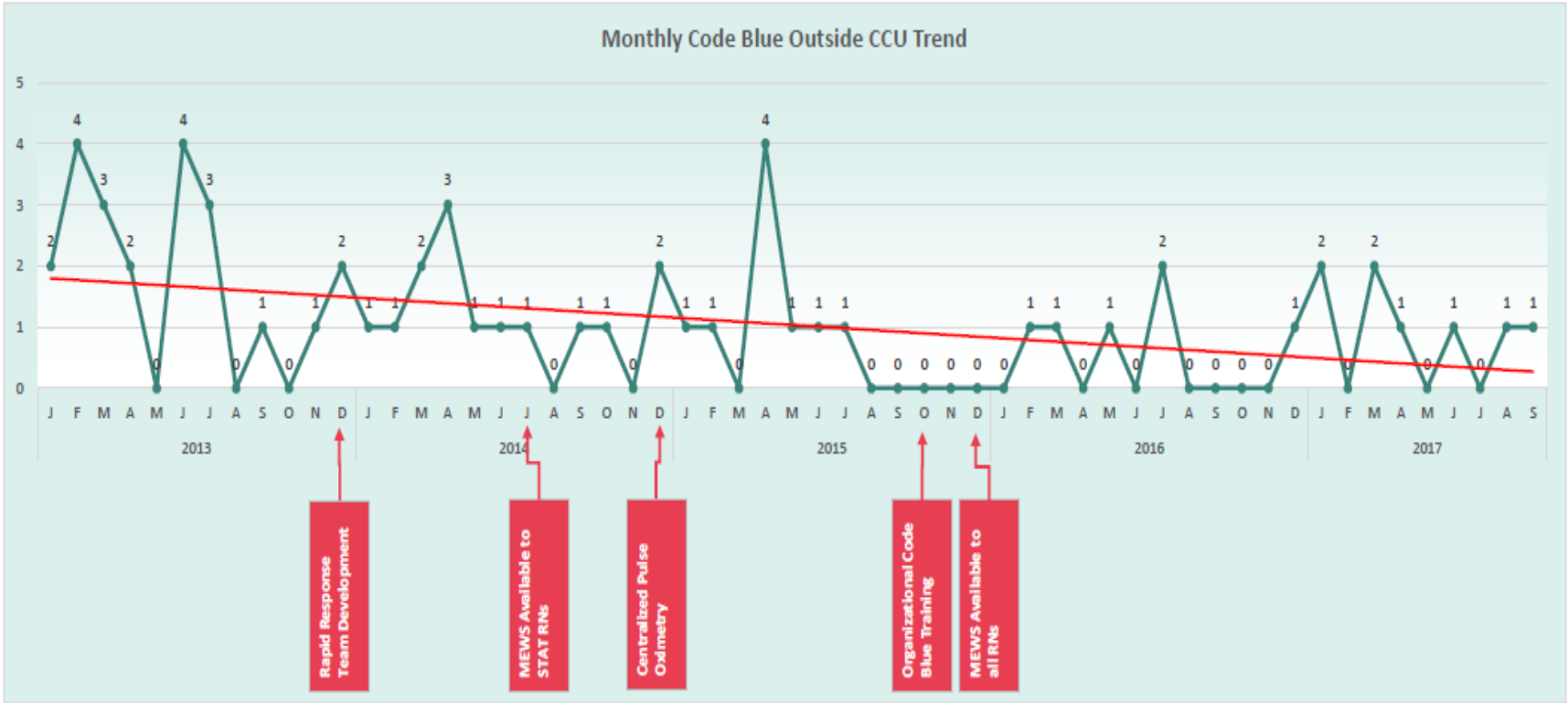
MEWS Score	Recommended RN Action Items
0-2	* Follow routine monitoring as ordered
3	* Assigned RN rechecks vital signs for accuracy * Collaborate with charge RN to reassess patient and confirm score * Consider increasing frequency of vital signs as appropriate
4	* Assigned RN rechecks vital signs for accuracy * Collaborate with charge RN to reassess patient and confirm score * Consider increasing frequency of vital signs as appropriate
5	* Assigned RN rechecks vital signs for accuracy * Collaborate with charge RN to reassess patient and confirm score * Consider calling Rapid Response * Inform Physician * Increase Vital Signs frequency to every 1 hours x3 and confirm score each time * If patient remains "5" for three consecutive readings, consider transfer to higher level of care
>=6	* Assigned RN rechecks vital signs for accuracy * Collaborate with charge RN to reassess patient and confirm score * Call Rapid Response and Physician STAT if physician is not already involved * Recommend transfer to higher level of care

Code Blue Outside the CCU



Maternal Early Warning Trigger (MEWT)

- Validated by the California Maternal Quality Care Collaborative (CMQCC)
- Screens for the four major causes of maternal morbidity
- Low false positive

Severe Abnormal Trigger: If any ONE (1) of these are present for greater than 20 mins - CALL PROVIDER IMMEDIATELY

- Heart Rate greater than 130 – Sustained, excludes pushing
- Respiratory Rate greater than 30
- Mean Arterial Pressure (MAP) less than 55
- Oxygen saturation less than 90% on room air
- Nursing is clinically concerned with patient status

Complete screening each shift or when patient's condition changes		Date Time						
		Initials						
Maternal Trigger	**Screening Criteria (Circle the identified trigger, as applicable)**	**Check all that apply below ↓**						
1. Temperature	Greater than or equal to 38°C / 100.4°F **OR** Less than or equal to 36 °C /96.9 °F	☐	☐	☐	☐	☐	☐	☐
If Maternal Temperature ONLY, Notify Provider. See Maternal Early Warning Triggers Algorithm on back of tool								
2. Fetal Heart Rate (sepsis path)	Greater than 160 bpm (*baseline, gestational age greater than or equal to 20 weeks)	☐	☐	☐	☐	☐	☐	☐
3. Maternal Heart Rate *Exclude during Pushing	Greater than110 bpm or less than 50	☐	☐	☐	☐	☐	☐	☐
4. Respiratory Rate	Greater than 24/min or less than 10	☐	☐	☐	☐	☐	☐	☐
5. 02 Saturation	Less than or equal to 94% on room air	☐	☐	☐	☐	☐	☐	☐
6. Blood Pressure	Systolic greater than 155 or less than 80 Diastolic greater than 105 or less than 45	☐	☐	☐	☐	☐	☐	☐
7. Pain	Sudden onset, increasing, unusual for diagnosis or normal clinical course, noted in new location	☐	☐	☐	☐	☐	☐	☐
8. Altered Mental Status	Confusion, agitation, combativeness, dizziness, shortness of breath	☐	☐	☐	☐	☐	☐	☐
Are any two (2) of the above present? If YES repeat assessment within 20 to 30 minutes. If trigger is sustained, CONTACT PROVIDER and consider the following appropriate pathway on the back of this screening tool. Continue with screening every 20 to 30 minutes, as indicated If "NO", STOP HERE till next assessment		☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No	☐ Yes ☐ No
Timing of Provider Assessment (for patients with ≥ 2 sustained triggers).		☐ <30min ☐ 31-60m ☐ >60min	☐ <30min ☐ 31-60m ☐ >60min	☐ < 30min ☐ 31-60m ☐ >60min	☐ <30min ☐ 31-60m ☐ >60min	☐ <30min ☐ 31-60m ☐ >60min	☐ <30min ☐ 31-60m ☐ >60min	☐ <30min ☐ 31-60m ☐ >60min

Additional Comments:
Was the triggers pathway followed? ☐ **Yes** ☐ **No**
Which trigger pathway selected (check all that apply) ☐ HTN ☐ OB Hem ☐ Sepsis ☐ Cardiopulmonary
Transferred to ICU? ☐ **Yes** ☐ **No** **LOS # Days in ICU:**_____
****Final status of this patient: (summarize below):**

Evergreen Health	Patient Label
Maternal Trigger Screening Tool (MEWT)	
Worksheet only – Not Part of Medical Record	

Rev 6-22-17

PILOT

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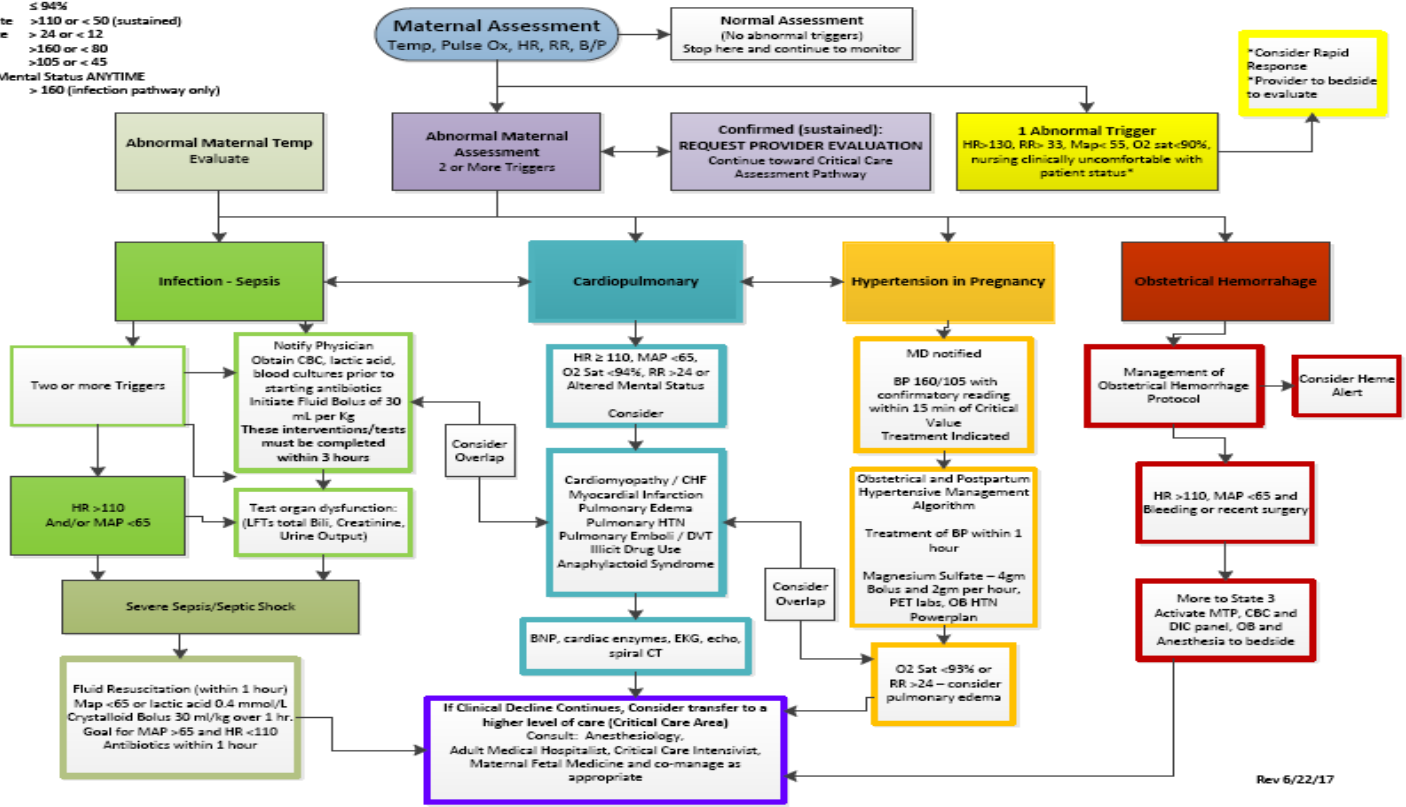
Flow Diagram for Maternal Early Warning Trigger (MEWT) Tool

Maternal Triggers

Temp	≥ 38°C (100.4°F) or ≤ 36°C (96.9°F)
02 Sat	≤ 94%
Heart Rate	>110 or < 50 (sustained)
Resp Rate	> 24 or < 12
Syst BP	>160 or < 80
Diast BP	>105 or < 45
Altered Mental Status	ANYTIME
Fetal HR	> 160 (infection pathway only)



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Emergency Severity Index (ESI) Score

- Used widely across the country to triage ED patients
- 1 to 5 levels- 1 requiring the most immediate attention (cardiac arrest) while 5 least attention (rash)
- 70% of patients are triaged to level 3 per research done on ESI
- Tool developed based on algorithm to predict a patient's severity of illness

best practices

Johns Hopkins uses electronic tool to improve triage of ED patients

By Maria Castellucci

Triage nurses in the emergency department at Johns Hopkins Hospital in Baltimore face a hard task. Just like in EDs across the country, they must decide in just a few minutes how critical a patient's condition is and assign them a score that will determine how quickly they are treated.

The nurses use the Emergency Severity Index to help make their decision. The ESI, a tool used widely in EDs across the U.S., is a way for caregivers to identify patients' conditions by assigning them to one of five groups, or levels. Level 1 indicates the patient needs immediate attention and is experiencing something along the lines of cardiac arrest, while Level 5 means their needs aren't urgent—a rash, for example.

That's important, obviously, because it gets the patient the right treatment more quickly. The problem is the ESI isn't always right and relies heavily on

STRATEGIES

Create a tool in the electronic health record that assigns patients an Emergency Severity Index score.

Ensure the tool uses an algorithm that includes the health information of patients previously treated at the system to improve accuracy.

would be "replaced by a computer."

"We were very resistant at first because for us, being trained as a triage nurse is an honor. It shows clinical excellence and that you understand clinical decisionmaking," she said.

Levin said he spent months with the triage nurses to ensure they understood that the tool was not to replace their clinical judgment but merely to support them in their work. Levin said he tells nurses they should disagree with the tool when they think it is appropriate. After all, the tool can't interact with patients the way a nurse can.

Levin, however, said he's confident in the tool's results because it's targeted at Johns Hopkins' unique patient population. He said healthcare tools that rely on algorithms aren't usually widely adopted because providers don't trust the data. But caregivers trust the accuracy of data used to develop this tool's algorithm.

The e-triage tool "is more mean-

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Administrative Application

Inpatient Staffing Demand

Emergency Department Demand Prediction

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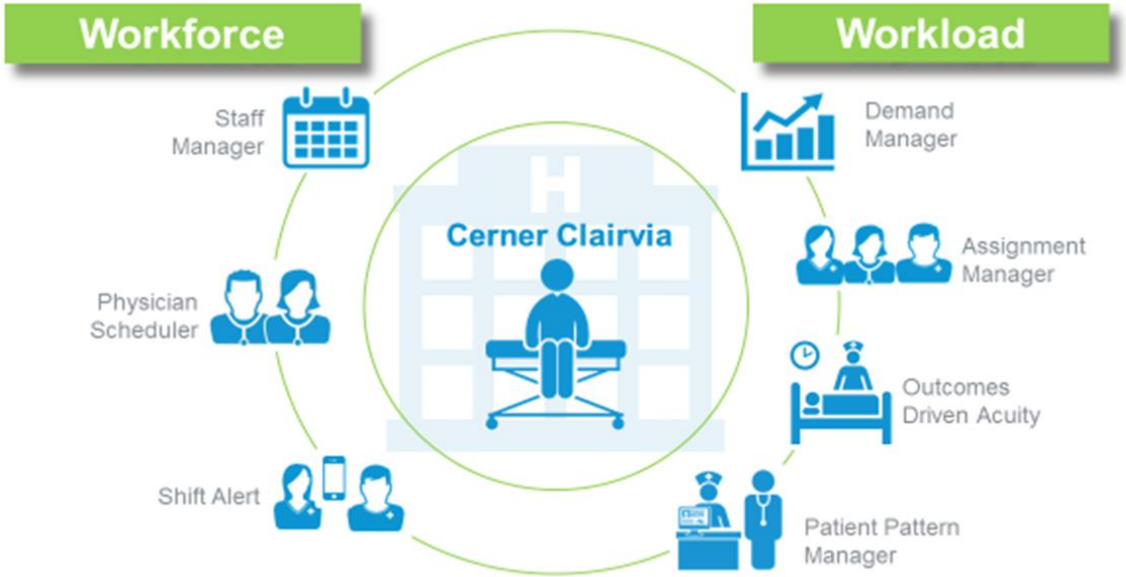
Inpatient Staffing Demand



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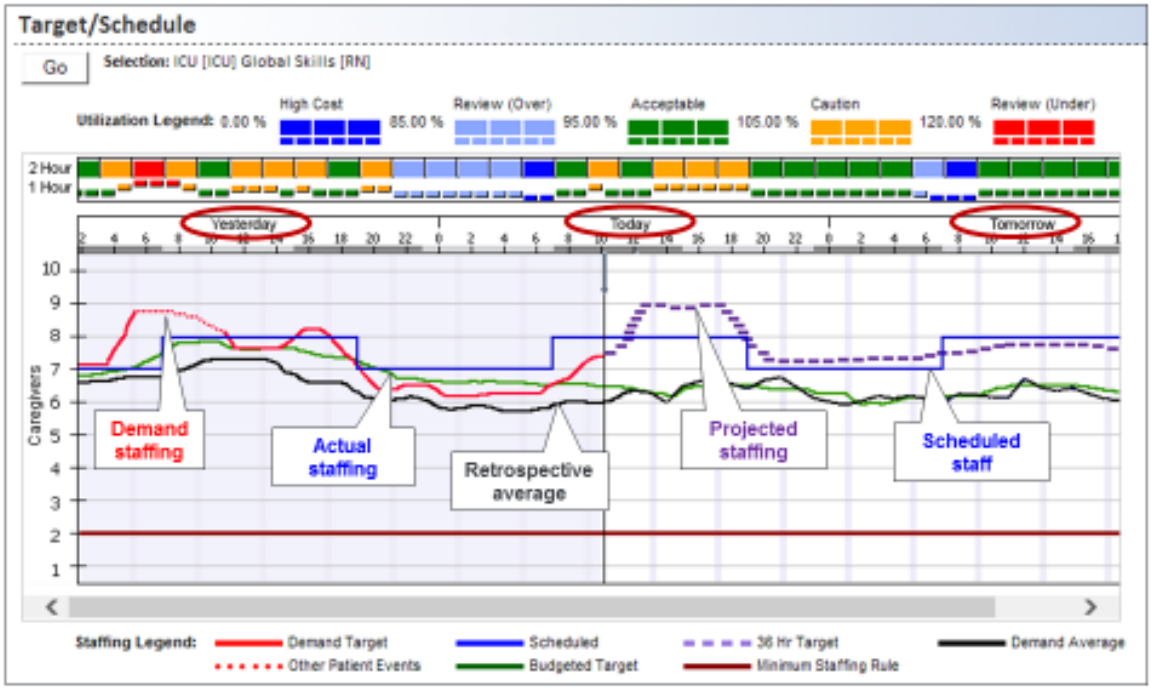
Intelligence of Efficient Staffing



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Managing the Cost of Nursing Efficiently

Better patient outcomes occur with the
right caregiver, at the **right place,** at the **right time.**

Six months after implementing
Cerner Clairvia

nursing overtime
and double time
dropped 8.4% and
saved 2,000 hours

Children's Hospital LOS ANGELES
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Emergency Department Prediction

- The KenSci product will provide the following KPI's:
- We will predict the number of patients arriving in the ED and their associated acuities within the next 2, 4, 6, and 8 hours, as well as at 1 and 6-month intervals
- We will provide the current and predicted average wait time in the waiting room and the median length of stay for patients in the ED

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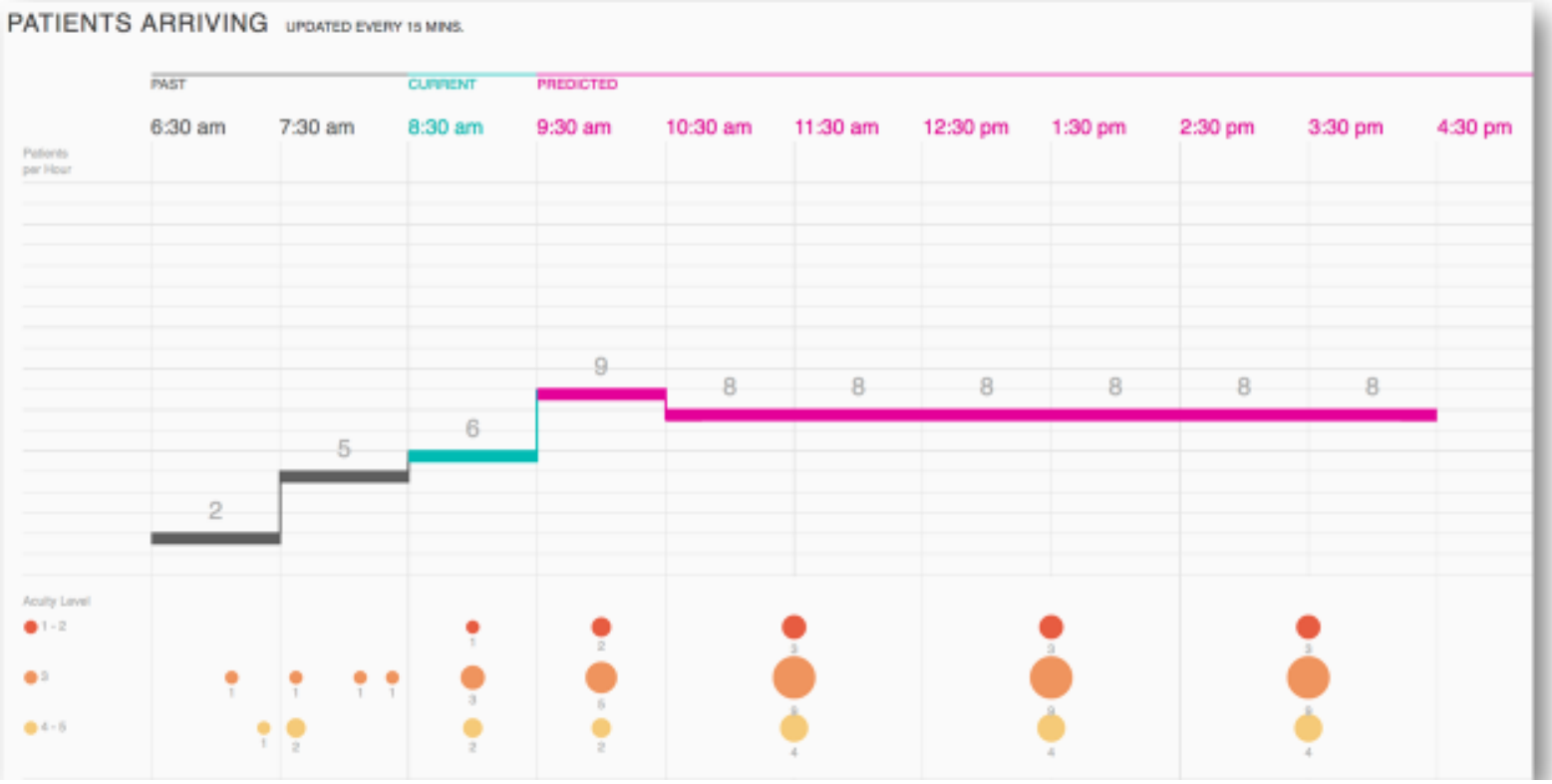
Real-time Prediction – Prediction only



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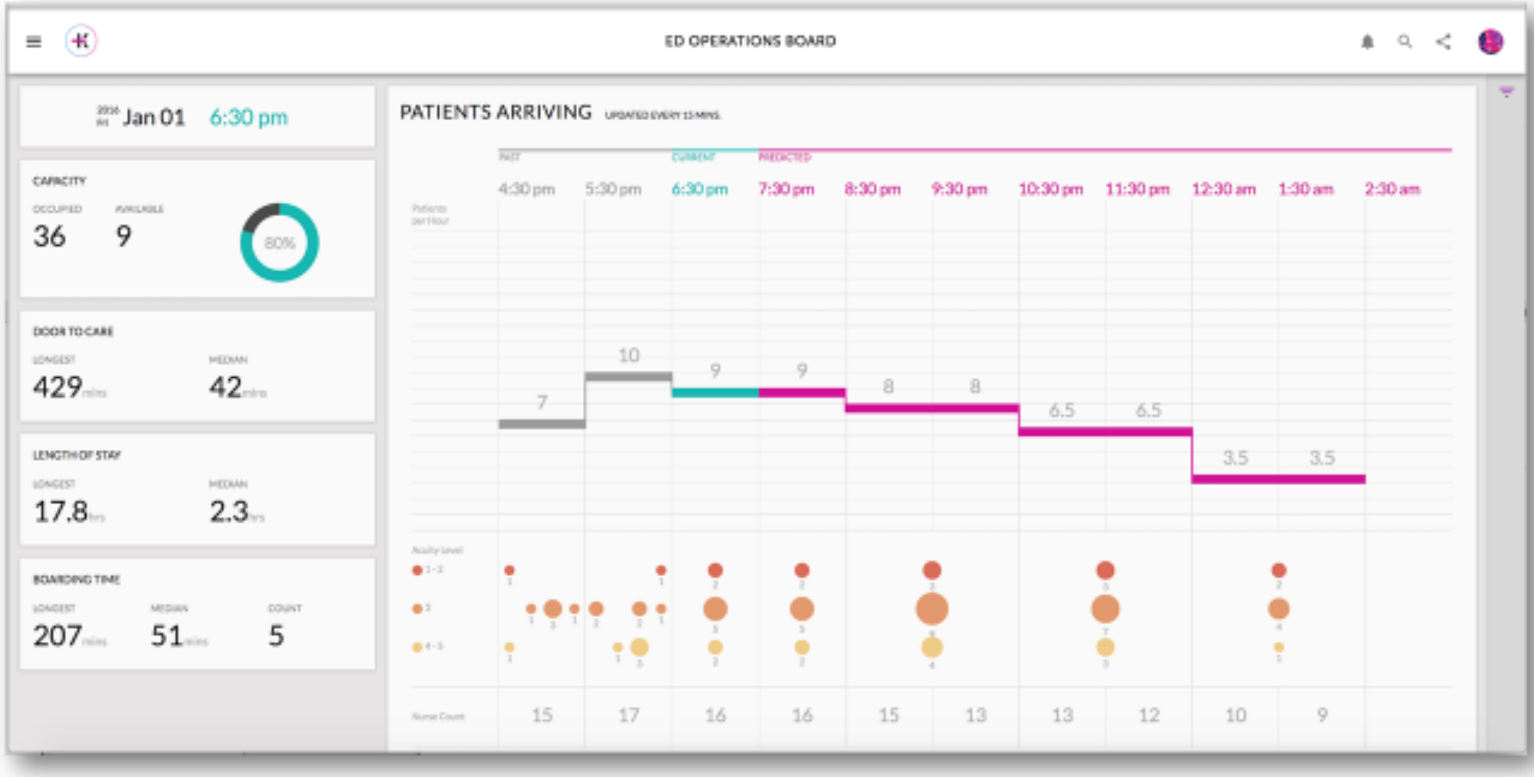
Real-time Prediction – Prediction and descriptive data display



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Long-term Prediction

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Educational Application

innovations

Software helps predict employee retention

By Rachel Z. Arndt

Turnover among healthcare and social assistance workers is on the rise, with the rate inching toward one-third annually. Not only is turnover disruptive, it's also resource-intensive, with providers spending tens of thousands on job searches and new employee training. Every time a nurse leaves and is replaced, for instance, a healthcare organization spends $37,700 to $58,400.

Part of the solution, according to data and analytics company Arena, comes upfront during the hiring process. Arena wants to keep providers from bearing the costs of turnover by improving retention rates. To do so, the company uses prediction models to cull from among a pool of applicants those most likely to stick with the job at hand and to be engaged, along with other metrics. Thanks to machine learning, the prediction models continu-

"Similar to the way Amazon uses your purchase data to predict what products you might want to purchase, Arena predicts how each person will improve outcomes like employee retention, patient satisfaction."

MICHAEL ROSENBAUM

Arena

job applicant assessments, how likely each applicant is to improve certain metrics—including retention.

For example, for a client with two facilities across the street from each other—one for long-term care and the other for acute care—the Arena assessment, which takes about 15 to 30 minutes, asked each applicant if he or she was a leader in a community organization. Those who said yes were more likely to stay in their jobs at the acute-care facility and more likely to leave the long-term care facility.

But Michael Finn, Arena's vice president of marketing, cautions against reading too much into individual questions, which may be more correlation than causation. Instead, Arena's predictions come from data models. "The results of the predictions are better than any single correlation," he said.

Since MultiCare Health System in the Pacific Northwest began using Arena in

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Nursing Turnover is Costly

- National Average 14%
- Magnet Hospital Average 11.90%
- Average Cost $85,000
- 14 nurses= $1,190,000
- 178 nurse =$15,130,000

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GNOSIS LOGIN

Prophecy Analytics

What sets Prophecy apart from other assessment tools is its ability to generate, aggregate, and analyze data to predict nurse success.

Unlike other solutions, Prophecy combines clinical, situational, and behavioral assessments to optimize analytics in three ways

measure competency + measure job fit + measure education gaps

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Clinical

Provides insight into job knowledge and critical skills you need a nurse to have on day one, specialty-by-specialty.

This Assessment Includes:

- Administering Medications
- Problem Solving
- Report Transitioning
- Critical Thinking
- Multitasking
- Assertiveness

Situational

Utilizes video simulations to assess how a nurse candidate would respond in various clinical scenarios.

This Assessment Includes:

- Patient Care
- Developing Patient Relationships
- Verbal Communication
- Patient Customer Service
- Patient Care Plan Management
- Conflict Resolution

Behavioral

Assesses individual personality attributes to help determine appropriate roles and the best-fitting specialty.

This Assessment Includes:

- Accountability
- Honesty & Conscientiousness
- Conflict Resolution
- New Technique Application
- Managing Patient Care
- Change Adaptation

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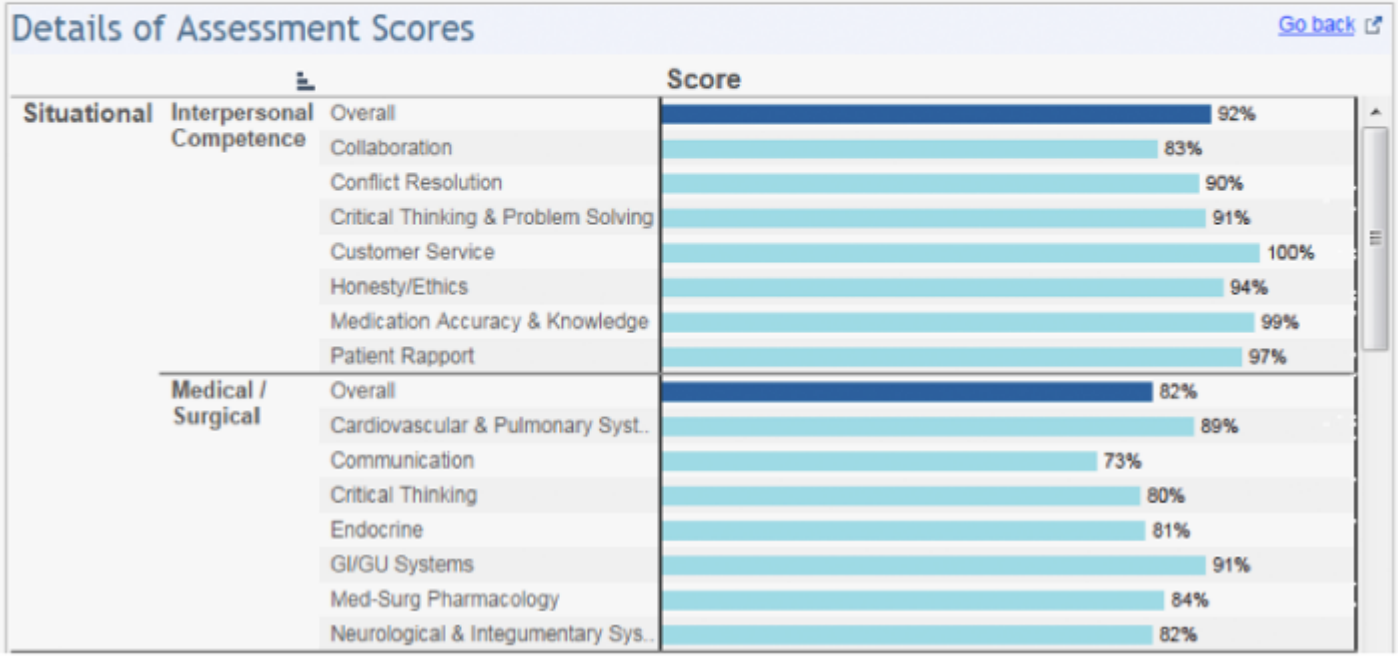
Where would training and education be needed?



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Which specialties are statistically a best fit?

Job Fit by Clinical Specialty

Sort by: Last name

	Best fit	Med/Surg	ICU	L & D	ER	NICU
Rasheed Andrew	ICU	73%	84%	78%	72%	33%
Renda Mary	ER	49%	19%	30%	94%	29%
Richmond Russ	ER	21%	29%	19%	86%	25%
Rose Lily	Med/Surg	95%	88%	34%	28%	18%
Rundquist Niklas	ER	33%	30%	15%	85%	33%
Sadler Felicia	Med/Surg	81%	22%	23%	75%	22%
sarbaugh steve	ER	15%	62%	58%	73%	33%
Schultz Laurel	Med/Surg	94%	55%	83%	19%	60%
Sofish Jandra	ICU	54%	95%	60%	18%	26%
Sonin Juhan	NICU	52%	85%	25%	61%	94%
Spangler Melissa	NICU	25%	21%	21%	80%	84%
Sparkman Lora	ICU	55%	95%	70%	44%	54%
Walcher Tony	ICU	29%	94%	73%	63%	21%
Warrier Divya	L&D	69%	61%	75%	57%	22%
Wiese Elaine	ICU	78%	94%	61%	75%	61%
Wright David	ICU	39%	65%	61%	29%	47%
Zabbix Jack	Med/Surg	71%	24%	33%	18%	25%
Zabbix Jill	ER	62%	60%	41%	63%	35%
Zalesky Petr	ER	26%	25%	26%	78%	60%

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Behavioral
assessments by Prophecy

Important Note

The report for the APS Behavioral assessment provides information about job applicants and/or employees in several different areas of interest. We recommend that the information contained within this report be viewed as only one source of information that can be used to help employers make decisions about potential (or existing) employees, and that no decision should be made based solely on the information contained within the report. Rather, we recommend using the results to identify areas that might benefit from further investigation during other portions of the selection or placement process, such as during an interview or during an applicant's background review.

Recipient Name:		**Company:**	**EvergreenHealth**
Date of Exam:	07/06/2017	Exam Name:	Personality, General Reasoning, Attitude, Engagement
Exam ID:	2A661539-39CC-499C-8E83-71A9BDAA075A		

Registered Nurse - Medical Surgical

Job Fit Score: 75%(1)

07/06/2017

General Reasoning

Favors repetitive tasks ◇ Favors complex intellectual challenges

- learns new information at an average pace
- Many med-surg nursing roles may provide ... with the ideal balance between routine issues and new challenges

Question: Tell me about a time when you felt overwhelmed with a large patient load. How did you handle it?
Question: Give me an example of a time when you struggled to interpret information in a patient chart. What happened?
Question: Describe a time when you only had partial information about a patient case. How did you handle it?

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Predictive Analytics: Key Takeaways

1. **Definition:**

   Computer analysis of data using knowledge to extract valuable patterns to inform decision making

2. **Nurses Role: *Use it!***
   - Comprehend, embrace, implement
   - Actionable, precision, decision making
3. **How Nurses add Value: Serve the Quadruple Aim**
   - Better manage populations + Lower costs
   - Improve the patient experience + Enhance nurse experience

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Predictive Analytics: Key Takeaways

- Helps improve quality and outcomes
- Individualizes patient care = The 4 Rights
- It's power is here right now and in the future
- Touches every nurse
- ***Cannot thrive in healthcare without nursing!***

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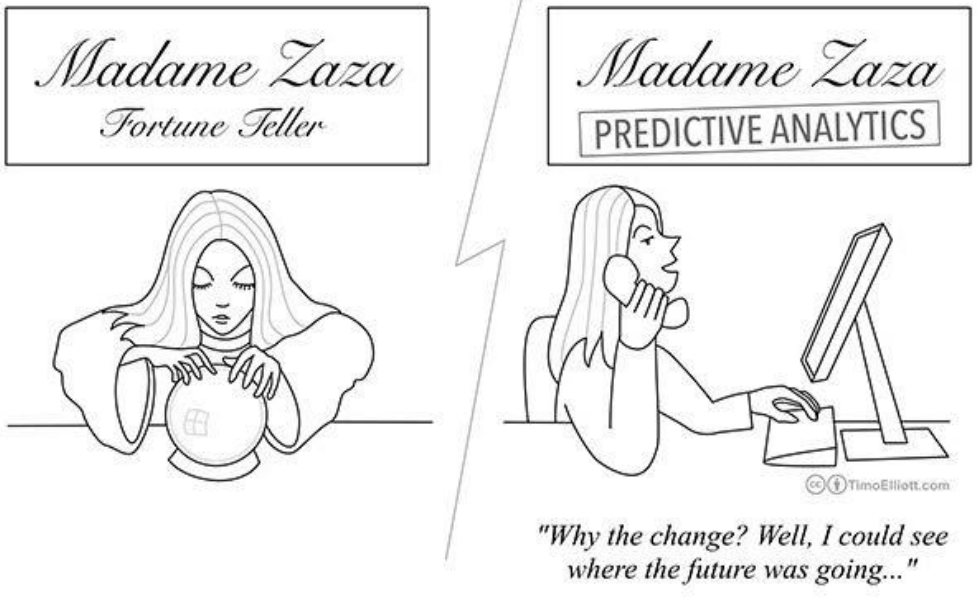
Predictive Analytics: Key Takeaways



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Questions

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Thank you! *Please complete online session evaluation*

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