Decision Support

APSF Sept 6th 2023

Kevin K. Tremper, PhD, MD Professor Department of Anesthesiology

CO

I have software patents granted (through the U of Michigan) regarding display technology.

I am the founder, President, investor and equity holder in AlertWatch, a University of Michigan Startup Company which has been acquired by BioIntelliSense for whom I am a consultant \$\$\$\$



Approximately 1 in 50 Surgical Patients (open procedures) will Die within One Month of Their Surgery

> Postoperative Mortality in The Netherlands

Noordzij et al, *Anesthesiology* 2010; 1105-15

CDC: Leading Causes of Death

1. Heart Disease 2. Cancer **3. Chronic Respiratory Disease** 4. Accidents 5. Stroke Etc.

CDC: Leading Causes of Death

- **1. Heart Disease**
- 2. Cancer
- 3. 30 Day Mortality after Surgery (190,000/yr)
- 4. Chronic Respiratory Disease
- 5. Accidents
- 6. Stroke

Etc.

Maternal Mortality is Rising in the U.S. As it Declines Elsewhere (Deaths per 100,000 live births)



The Lancet, 2015

Automated Decision Support May Help

Types of DS

1. Automating Calculations/Alerts to improve standardization (live calculations)

- 2. Escalating alerts to help us follow out own protocols (following our own rules)
- 3. Providing alerts/recommendations we could not determine manually (Machine learning/Al driven)

"Life is like a box of chocolates"



My professional life in a nutshell

1975 to 1978 "If you would like to apply Eng to Med you should go to Med School and study continuous noninvasive O2 monitoring" Irv Fatt UC Berkeley & John Severinghaus UCSF

1978 to 1981 "If you would like to study monitoring & outcomes in sick people, come work in my SICU" Will Shoemaker

1990 to 2000 "If you want to collect lots of clinical data, make an electronic anesthesia record" Mike O'Reilly and I at U of M with SEC Inc (Vic & Sachin Kheterpal)

2008 to today "If you want to do large observational research to determine periop risk factors, add multiple institutions" Sachin Kheterpal, Nirav Shah, Michael Mathis and the entire MPOG group

2008 to today "If you want clinicians to know who, where and when to apply this new knowledge, you need a decision support/alerting system. AlertWatch

etianCaptain Henry "Steve" Tremper WW2



J-3 Cub, 1966:Downington PA "Don't fly over anything you can't land on."











1960's - 1970's Cockpit, Crash 1:1,000,000



"Glass Cockpit," Crash 1:16,000,000



Integrated Avionics Screen



AlertWatch Draft 2007



AlertWatch Draft 2007



Add Colors



1. Automating Calculations/Alerts to improve standardization (live calculations)



Monitors

AW Multifunctional Monitor, 2011





Decision Support Engine



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Working Prototype 2011 Lets do a study



IRB Questions:

Is it FDA Cleared ? What ???

If it is turned on and off every two weeks ... You need patient informed consent

"We have developed a new software safety system, we don't know if it helps, is it OK if we turn if off for you?"

FDA MDDS 2011 (updated Sept 2022)

 Non-Regulated (MDDS): "Solely intended to transfer, store, convert format, display device data including waveforms"

 Regulated MDDS, 2011: "Software functions to analyze or interpret device data in addition to" (this is an MDDS Class II software device)

FDA Guidance Documents 2011-2022



Your Clinical Decision Support Software: Is it a Device?

FDA

Your Clinical Decision Support Software: Is It a Device?

The FDA issued a guidance, Clinical Decision Support Software, to describe the FDA's regulatory approach to Clinical Decision Support (CDS) software functions. This graphic gives a general and summary overview of the guidance and is for illustrative purposes only. Consult the guidance for the complete discussion and examples. Other software functions that are not listed may also be device software functions. *



*Disclaimer: This graphic gives a general overview of Section IV of the guidance ("I

discussion. The device examples identified in this graphic are illustrative only and are not an exhaustive list. Other software functions that are not listed may also be device software functions.

Study on hold ... FDA??

U of Michigan's Business Engagement Center's recommendations:

- 1. Get patents, we'll do that
- 2. Find a CEO, we'll help with that
- 3. Raise \$\$, you do that

5 years and \$500K later we received FDA Clearance

AW decision support analysis/calculation

Examples:

- 1. I&O balance
- 2. Estimated Hb
- 3. Cumulative Hypotension4. PPH Risk

FDA?



What's with the yellow? Show us the published yellow ranges

Air Traffic Control



Flight Tower View : Wash U "ACTFAST"

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U-OR 01 In Room		15:39 R1	U-OR 04 Surgery	-	Khat Patt 15:41 R1	U-OR 05 Surgery	-	Khat Denn 16:12 R0	U-OR 06 In Room	Peop Hows 16:56 R0	U-OR 07 Surgery	-		Mine 14:2	Lin 0 R0
U-OR 08 Surgery		Mine Vido 13:08 R1	U-OR 10 Surgery	-	Buko Lauz 11:02 R0	U-OR 12 Surgery	-	Chan Murp 15:13 R0	U-OR 13 Surgery	Youn Swet 15:13 R0	U-OR 16 Surgery	-	C)avi 1 14:2	исВr 2 R0
U-OR 17 In Room	•	Davi Shah 15:56 R1	U-OR 21 In Room		Kril LoRe 17:29 R1	U-OR 27 Surgery	-	Chan Baet 14:15 R0	U-OR 28 Surgery	Sarg Bell 14:24 R1	U-OR 31 Surgery	-	М	oor F 14:0	(ram 9 R0
U-OR 32 Surgery	-	Moor Leve 16:09 R1	U-OR 33 Surgery	-	Szoc Tawf 14:46 R1	U-OR 34 Surgery 9 §	-	Chiw Thar 12:25 R1	U-MPU A Surgery	Demb Labo 14:05 R0	U-MPU B Surgery	•	De	emb 14:3	Locu 0 R0
U-MPU F Surg End S (C)	-	11:41 R0	U-MPU G Surg End	-	12:51 R0	U-MPU K Surg End	-	13:19 R0	U-MPU N Surgery	Keit Iaco 14:17 R0	ANAISYS-0 Induction	6		12:2	4 R0
IVF 01 Induction	-	12:42 R0													



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Input / Output Ba	nput / Output Balance ×											
Estimated Blood Volume = 3810 mL												
I/O Balance	= Added Fluid	- Insensible Loss	- EBL x 3	- Surgery Loss	- Urine Total	±	Norma	lize				
-451	+ 1500	- 1351	0	0	- 600		0					
Added fluid = cry	stalloid (1500) + colloid	(0) x 3 + albumin (0) x 1.5	+ PRBC (0) x 3 ·	+ cellsaver (0) x 3								
Insensible loss =	[NPO until incision (8.7	7) + surgery hours (4.7)] x w	veight factor (101	1)								
Weight factor = • 40 + weight if w • 20 + 2 x weight • 4 x weight if we EBL (0) Surgery loss = th Normalize = man	Weight factor = • 40 + weight if weight > 20 • 20 + 2 x weight if weight > 10 • 4 x weight if weight \leq 10 EBL (0) Surgery loss = third space loss (0) x weight (61.2) x surgery hours (4.68)											
I/O Settings	I/O Settings I/O Balance References											
Normalize			<u>Crysta</u> Require	alloids Versus Colloids: E	Exploring Differences	in Flui	<u>d</u>					
NPO Time (hours)	NPO Time (hours): Summary											
9	9 Cortés, Anesthesia & Analgesia, 2015											
	Arterial Pressure Variation in Elective Noncardiac Surgery: Identifying Reference Distributions and Modifying Factors Summary											
3rd Space Loss:	3rd Space Loss: Mathis, Anesthesiology, 2017											
None			 <u>Restric</u> 	ctive versus Liberal Fluid	<u>d Therapy for Major A</u>	bdomi	inal Sur	<u>gery</u>				
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Prediction of blood volume in normal human adults

To fit the data, he used an "IBM electric digital computer" ... "a Herculean task by any other method"

EBV= 0.3669xH³ + 0.03219xW + 0.6041 (for men)

Nadler et al Surgery 1962

Estimated Hct





Maximum Blood Savings by Acute Normovolemic Hemodilution Feldman et al Anesth & Analg 1995



Solve for Hct_m



Estimated Hct = Hct / (e EBL/EBV) + added blood EBL = Estimated Blood Loss EBV = Estimated Blood Volume



Keep MAP > 55 mmHg or 60 mmHg Cumulative BP

A. Postop Renal Injury B. Postop Myocardial Injury



Relationship between Intraoperative Mean Arterial Pressure and Clinical Outcomes after Noncardiac Surgery... Walsh et. al., *Anesthesiology, V 119 No 3, 2013.*

AW Cumulative Hypotension



ANESTHESIOLOGY

Preoperative Risk and the Association between Hypotension and Postoperative Acute Kidney Injury

Michael R. Mathis, M.D., Bhiken I. Naik, M.B.B.Ch., Robert E. Freundlich, M.D., M.S., M.S.C.I., Amy M. Shanks, Ph.D., Michael Heung, M.D., Minjae Kim, M.D., Michael L. Burns, M.D., Ph.D., Douglas A. Colquhoun, M.B. Ch.B., M.Sc., M.P.H., Govind Rangrass, M.D., Allison Janda, M.D., Milo C. Engoren, M.D., Leif Saager, M.D., M.M.M., Kevin K. Tremper, M.D., Ph.D., Sachin Kheterpal, M.D., M.B.A., on behalf of the Multicenter Perioperative Outcomes Group Investigators*

ANESTHESIOLOGY 2020; XXX:00–00



Mathis et al Anesthesiology March 2020

6 Years of Observational Experience; Feb 2018 Kheterpal S, Shanks A and Tremper K



Decision Support Alerts and Risk Prediction Tools: Harnessing Data to Improve Patient Outcomes

AlertWatch User vs Non-User 6 yrs and 26,769 cases

Process Measures:	P values
Hypotension < 55 mmHg *	<0.001
Crystalloid ml/kg/hr	<0.001
Tidal Volume 6-8 ml/Kg Ideal BW	<0.001

Clinical Outcomes (Historical vs Parallel): MI 1.5% vs 2.6% vs 2.1% ... Versus no difference AKI ... No difference Resource Differences: LOS 5 days vs 6 days <0.001 Hospital Charges \$3,603 less for AW patients 2. Escalating alerts to help us follow out own protocols (following our own rules)

Maternal Decision Support for L&D

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53 G6P4	TR	BMI 39 GA 35+2	62 G3P2	TR	BMI 30 GA 0+0	29 G2P1 = 16	AP	BMI 30 GA 36+0	31 G6P2 ❶ 韋 ≧	AP 20 🧲	BMI 25 GA 32+2	30 G4P2 ∳ ♦	AF 18 +++	•	BMI GA 29+;	0 2
35 G3P0 ₩	AP	BMI 34 GA 30+1	26 G1P0 🗎 18	L-3 cm	BMI 47 GA 37+4	04 G3P2 = 18	L-7 cm	BMI 25 GA 37+0	27 G7P5 9 🦳 🌢	L	BMI 59 GA 38+1	58 G4P2 🕑 🌪	L	•••	BMI 33 GA 0+	5 0
00 G2P1 C 18	L-10 cm	BMI 25	10 G1P0 9 e	L-10 cm	BMI 25	13 G2P1 了 e	L-10 cm	BMI 27	28 G3P3 ❶ ● 14	PP	BMI 33	33 G7P3	PP		BMI 3	7
48 G7P6 ❶ ♠	PP	BMI 30	47 G2P2 ❶ ♦	PP-CD	BMI 35	34 G2P2 9 (*	PP-CD	BMI 54	32 G5P4 😄 🗎 16	PP-CH	BMI 28					
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Triage	Triage Antepartum Labor Stage 2 or 3 Postpartum Readmit Fetal Loss (Click for full icon legend description) 19 / 20															

Tom Klumpner et al A&A Feb 2020

AWOB PPH Risk/PPH/Preecampsia



ACOG PPH Risk Factors Checks IV size and Blood availability

		AlertWatch Demo	- Click to exit					
PH Risk Factors/Obstetric Cormorbidities								
High Risk PPH Placenta Accreta Placenta Increta Placenta Percreta Placenta Previa Bleeding Before Delivery Known Coagulopathy Platelet Count < 70k Two or more medium risks	Mee SBI Cl Fe Mi Mi O P P Pr Pr Pr	dium Risk PPH MI > 40 horioamnionitis etal Macrosomia ematocrit < 30 agnesium Sulfate ultiple Gestation yoma xytocin > 24 hours arity > 4 for C/S or Uterine Surge for Postpartum Hemorrh rolonged 2nd Stage	ery lage	Other Risk Factors Group B Streptococcus Positive HELLP Polyhydramnios Preeclampsia Severe Preeclampsia Vasa Previa No risk factors documented				
12 hours 24 hours 3 days 7 days	Current Visit							
12		No data to d	lisplay					
0- 2:00 pm 2:	5 pm	2:30 pr	n	2:45 pm	3:00 pm			

AWOB PPH Risk/PPH/Preecampsia



HR, BP, Hb & Shock Index to Alert For Postpartum Hemorrhage



AWOB Paging Logic for: Hypotension * Hypertension Tachycardia Shock Index * Anemia *



"Algorithm" to Remove Artifacts



"PPH Risk Confirmed: "Rm 18. Systolic BP 55 "



Frequency of Paging Alerts / 24 hrs. (50-bed L&D Unit)

	ME	WC	AWOB: RN Pages	AWOB: MD Pages
BP < 90	12.8	BP < 85	6.4	0.96 (< once a day)
BP > 160	10		11	2.8
BPd > 100	14.5	BPd > 110	5.3	0.4
HR > 120	51	HR > 130	23.8	2.1
Total	150 (every 8 min)		47	6.3 (every 3.8 hrs)

Klumpner et al BMC Anesthesiology 2018

Use of a Novel Electronic Maternal Surveillance System and the Maternal Early Warning Criteria to Detect Severe Postpartum Hemorrhage

Thomas T. Klumpner, MD,*† Joanna A. Kountanis, MD,*† Sean R. Meyer, MBA,‡ Justin Ortwine, BS,* Melissa E. Bauer, DO,*† Alissa Carver, MD,† Anne Marie Piehl, MSN, RN, CNM,‡ Roger Smith, MD,† Graciela Mentz, PhD,* and Kevin K. Tremper, PhD, MD*

Comparing AWOB Paging Alerts to MEWC: Does it Work?

7,853 Deliveries (over 20 months)... 120 sPPH events (1.5%)

PPH = EBL > 1,000 ml

sPPH = > 4 units PRBCs >2 PRBCs+ > units FFP Return to OR PP Hysterectomy Uterine Artery Embolism Admission to ICU

Klumpner et al A&A Feb 2020

AWOB vs MEWC*

 Table 3. Test Characteristics of Automated Pages Versus Maternal Early Warning Criteria for Severely

 Morbid Postpartum Hemorrhage

	Automated Paging System	Maternal Early Warning Criteria ^a	P Value ^b
	Estimate (95% CI)	Estimate (95% CI)	
Sensitivity	60.8% (52.1–69.6)	75.0% (67.3–82.7)	.027
Specificity	82.5% (81.7-83.4)	66.3% (65.2–67.3)	<.001
Positive predictive value	5.1% (4.0-6.3)	3.3% (2.7–4.0)	.007
Negative predictive value	99.3% (99.1–99.5)	99.4% (99.2–99.6)	.358

*This assumes that there is 100% response rate of escalation of care when MEWC are met

Klumpner et al A&A Feb 2020

AWOB vs MEWC*

Table 3. Test Characteristics of Automated Pages Versus Maternal Early Warning Criteria for Severely Morbid Postpartum Hemorrhage

Automated Paging System Maternal Early Warning Criteria^a Estimate (95% CI) Estimate (95% CI) Automated Pages Versus Maternal Early Warning Criteria

Pos Nei **Automated Paging System** Estimate (95% CI)

> 60.8% (52.1-69.6) 82.5% (81.7-83.4) 5.1% (4.0-6.3) 99.3% (99.1-99.5)

Maternal Early Warning Criteria^a Estimate (95% CI) 75.0% (67.3-82.7) 66.3% (65.2-67.3) 3.3% (2.7-4.0) 99.4% (99.2-99.6)

P Value^b

Klumpner et al A&A Feb 2020



"The automated system identified 10 of 120 deliveries complicated by sPPH not identified by the MEWC. Using an automated alerting system in combination with a labor and delivery unit's existing nursing-driven early warning system may improve detection of sPPH."

Klumpner et al Anesth & Analg, Feb 2020

3. Providing alerts/recommendations we could not determine(Machine learning/AI driven)

Epic's Sepsis Model (ESM) Issues ... Controversial

- 38,455 admissions (Retrospective)
- 2,552 (7%) had sepsis ESM =>6
- ESM identified 183 of these (7%) ROC = 0.63
- ESM missed 1,709 (67%) ... despite generating 6,971 alters (18% of all pts)
- ie 109 alerts to identify one septic pt.

• Wong et al JAMA Int Med Aug 2021 181(8) 1065-1070

Epic's Sepsis Model (ESM) Issues ... Controversial

- 11,512 admissions (Before vs After study)
- 10.2% has sepsis, ESM => 5
- ROC = 0.83
- Mortality 11.9 % to 10.1 %

• Cull et al Crit Care Explor July 2023

Machine Learning/Al How will the FDA handle this?

Clinical studies... and any revision will require a resubmission... unless you request and have it approved

A "Predetermined Change Control Plan"

My opinion...

Not an issue of insufficient analysis ... Machine Learning/AI

Its insufficient accurate high-resolution data...



KEY POINTS

- Question: How well do automated pages generated by a novel maternal electronic surveillance system and the Maternal Early Warning Criteria (MEWC) detect severely morbid postpartum hemorrhage (sPPH)?
- Findings: While neither system was completely sensitive, the automated system was more specific and identified 10 of 120 deliveries complicated by sPPH that were not identified by the MEWC.
- Meaning: Using an automated alerting system in combination with a labor and delivery unit's existing nursing-driven early warning system may ultimately improve detection of sPPH.

Try Live Demo

Fundamental Claims for Translational Research

"Studies suggest that it takes an average of 17 years for research evidence to reach clinical practice."

> Balas, E. A., & Boren, S. A. (2000). Yearbook of Medical Informatics: Managing Clinical Knowledge for Health Care Improvement. Stuttgart, Germany: Schattauer Verlagsgesellschaft mbH.

"It takes an estimated average of 17 years for only 14% of new scientific discoveries to enter day-to-day clinical practice."

> Westfall, J. M., Mold, J., & Fagnan, L. (2007). Practicebased research - "Blue Highways" on the NIH roadmap. JAMA, 297(4), p. 403.