THE TECHMED EVENT PERSONALISED EHEALTH FOR SUSTAINABLE HEALTHCARE

To develop intelligent, personalized technologies Dr. Tom Hueting - Evidencio

THE TECHMED EVENT PERSONALISED EHEALTH FOR SUSTAINABLE HEALTHCARE



DISCLOSURE SLIDE

Employee at Evidencio B.V.

The Evidencio platform

Bridging the gap between scientific output and clinical implementation



What is a medical algorithm?





Any **calculation**, **formula**, statistical **survey**, **nomogram** or **look-up table** useful in healthcare. Can contain **heterogeneous** and **multimodal** data



Include **decision trees** and **tools** for reducing or defining **uncertainty**.

Prediction model lifecycle







New article: "Development and validation of a prediction model for outcome X in patients with disease Y"

Development and **Validation** of a **Prediction** Model for Hepatitis B Virus-Related Hepatocellular Carcinoma Patients Receiving Postoperative Adjuvant Transarterial Chemoembolization.

Tu X, Zhang J, Li M, Lu F, Wang T, Gong W, Xiang B. J Hepatocell Carcinoma. 2023 Oct 24;10:1881-1895. doi: 10.2147/JHC.S422565. eCollection 2023. PMID: 37901717 Free PMC article.

Development and **Validation** of a Nomogram for Renal Survival **Prediction** in Patients with Autosomal Dominant Polycystic Kidney Disease.

Wang X, Zheng R, Liu Z, Qi L, Gu L, Wang X, Zhu S, Zhang M, Jia D, Su Z. Kidney Dis (Basel). 2023 Jun 6;9(5):398-407. doi: 10.1159/000531329. eCollection 2023 Oct. PMID: 37901714 Free PMC article.

Development and validation of a nomogram for predicting pulmonary

complications after video-assisted thoracoscopic surgery in elderly patients with lung cancer. Zhao D, Ma A, Li S, Fan J, Li T, Wang G. Front Oncol. 2023 Oct 13;13:1265204. doi: 10.3389/fonc.2023.1265204. eCollection 2023.

PMID: 37901337 Free PMC article.

Development and validation of a nomogram for preoperative prediction of

Box 1: Full PREP prognostic models to calculate the risk of adverse maternal outcomes in women with early onset pre-eclampsia

a. Risk at various time points from diagnosis until 34 weeks' gestation using the survival model (PREP-S) $S_{(t)} = S_0(t)^{\$} \wedge exp((\beta_1 * X_1 + \dots + \beta_n * X_n)) S_{(t)} = S_0(t) \wedge exp(-0.031*maternal age + 1.514*((Log(GA at the second s$ diagnosis/10))⁻² - 0.8345136) + 5.707*((Log(GA at diagnosis/10))^{-2*} ln(log(GA at diagnosis/10)) - 0.0652155) + 0.122 (exaggerated tendon reflexes) - 0.169 (one pre-existing medical condition) - 0.384 (two or more pre-existing medical conditions) + 0.016*systolic blood pressure + 0.797 (oxygen saturation < 94% on air) -0.002*platelet count + 0.126*log(alanine amino transferase) + 0.605*log(serum urea)² - 0.144*log(serum urea)³ + 0.265*log(serum creatinine) + 0.080*log(protein creatinine ratio) + 0.176 (baseline treatment with any antihypertensive) + 1.066 (baseline treatment with magnesium sulfate)) § S₀(t) - baseline survival adjusted for optimism at time t S 0 (48 hrs) = 0.99142, S 0 (72 hrs) = 0.98542, S 0 (1 week) = 0.96492, S 0 (1 month) = 0.87377 b. Overall risk by postnatal discharge using the logistic model (PREP-L) Probability (maternal adverse outcome) = $\exp(X)/(1 + \exp(X))$, Where X = -1.507-0.020*maternal age + 12.052*(log (gestational age))³ - 39.90241) - 7.930*((log (gestational age))³⁺log(log (gestational age) -49.08188) - 0.330 (if one pre-existing medical condition) - 0.579 (if two or more pre-existing medical conditions) + 0.146*log (urine protein creatinine ratio) - 0.951*(log (serum urea)⁻¹) - 0.004*platelet count + 0.024*systolic blood pressure + 0.409 (baseline treatment with antihypertensive) + 1.252 (baseline treatment with magnesium sulfate) Predictor value is 1 when present and 0 when absent



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https://www.evidencio.com/models/show/1043



Estimated risk of positive surgical margins: **15%**

	Problem definition		Data collection	Development	Validation & update	Impact assessme	nt	Clinical adoption
Show validation data	is:			(lear data)	ResultsRows included1000C-index0.792Brier score0.172Scaled Brier score0.24	95% CI: 0.7625 - 0.8204 ROC	Slope Intercept Hosmer-Lemeshow GOF	1.123 -0.046 0.153
Prepare Maintail 1 No 2 Yes 3 No 4 Yes 5 Yes 6 Yes 7 No 8 Yes 10 Yes 11 No 12 Yes 13 Yes	Present Negati T2 Absent Negati T2 Absent Negati T1 Present Positive T1 Absent Positive T1 Absent Positive T1 Absent Negati T1	Supplicition Supplicition<	Positive Presente Philooget are Positive Present Ductal Negati Absent Other Negati Absent Ductal Negati Absent Ductal Negati Absent Ductal Negati Present Ductal Negati Present Ductal Negati Present Ductal Negati Present Ductal Positive Absent Lobular Positive Absent Lobular Positive Present Lobular Positive Present Ductal Negati Present Ductal Negati Present Ductal Negati Present	Clear data Curronk Biston Positive O.0452 Elston Negati O.1561 Elston II Positive O.1561 Elston II Negat O.318 Elston II Negat O.318 Elston II Negat O.2600 Elston II Negat O.2774 Elston II Positive O.5531 Elston II Negat O.2600 Elston II Negat O.2774 Elston II Negat O.2501 Elston II Negat O.2561 Elston Negat O.2561 Elston Negat O.2561	Classification plot	- Sensibility - 1 - Specificity - 1 - Specificity - 1 - Specificity - Sensibility - Se	Calibration plot	- Adverses - Bitad roposcion line www.endencia.org - Adverses - Bitad roposcion line www.endencia.org - Adverses - Bitad roposcion line www.endencia.org - Adverses - Bitad roposcion line - B
14 Yes 15 No 16 No 17 Yes 18 Yes 19 No	Present Negati T2 Absent Negati T2 Present Negati T1 Present Positive T1 Absent Negati T2 Absent Positive T1	50-75% Non-P No 0-25% Non-P No 25-50% Non-P Yes 50-75% Non-P No 75-10 Palpa Yes 25-50% Palpa No	Positive Present Ductal Positive Absent Other Positive Absent Lobular Positive Present Ductal Positive Present Other Negati Present Other	Elston II Negati 0.314 Elston I Positive 0.1242 Elston II Positive 0.5717 Elston I Positive 0.4618 Elston I Negati 0.2047			Hereit Hereit	Threshold









Use the Evidencio platform to assess the impact of your prediction model



Evidencio can act as a legal manufacturer for your medical device software

Involvement in the prediction model lifecycle



Evidencio's Algorithm library



A showcase example of the collaboration with the University of Twente:

The NABOR project

INFLUENCE 2.0 -> INFLUENCE 3.0

Breast Cancer Research	and Treatment (2021) 189:817–826					
https://doi.org/10.1007/s10549-021-06335-z						

Check for

Improved risk estimation of locoregional recurrence, secondary contralateral tumors and distant metastases in early breast cancer: the INFLUENCE 2.0 model

Vinzenz Völkel¹ · Tom A. Hueting^{2,3} · Teresa Draeger¹ · Marissa C. van Maaren^{3,4} · Linda de Munck⁴ · Luc J. A. Strobbe⁵ · Gabe S. Sonke⁶ · Marjanka K. Schmidt⁷ · Marjan van Hezewijk⁸ · Catharina G. M. Groothuis-Oudshoorn³ · Sabine Siesling^{3,4}

the risk for DM. Table 3 gives an overview of the underlying coefficients.

Comparison to the original INFLUENCE nomogram and other related prediction models

Online calculator

r based on the se dictions s; an easy-to-use online risk calculator is https://www.evidencio.com/models/show/2238 sulator estimates the risks and the 95% conf 200 bootstranney

Compared to the original INFLUENCE nomogram, the INFLUENCE 2.0 model comes with a variety of updates leading to improved flexibility and a broader application range regarding predictable events. Concerning clinical decision-making, discrimination is arguably the most relant indicator for model performance. The AUC of the we annual prediction models of the original INFLUENCE nomogram which is exclusively concentrating on the endpoint LRR starts with 0.84 for the first year and decreases to

LOT V-2.0-2238.21.05.14 (F

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