

Clinical Prediction Rules

 Clinical prediction rules are algorithmic decision tool (that uses parsimonious clinical findings) designed to aid clinicians in determining a diagnosis, prognosis, or likely response to an intervention.



Glynn P, Weisbach C. Clinical Prediction Rules: A Physical Therapy Reference Manual. 2010.

JMMT 2008

EDITORIAL

Potential Pitfalls of Clinical Prediction Rules

What Jee Clinical Prediction Index² A chiral prediction real (CPR) in a constraint of the constraint nitrations statistical startholds on equiphiload in the spectrum with effective of the equiphiload in the sings of clinical variables? The use population provideva validation (He CPR is a provideva validation (He CPR is a significant on the predictive fiscance developed in the predictive fiscance developed in the predictive fiscance developed in the contrast of the CPR is an example of the interval of the CPR is toporese care on state and accurate developed definition of the CPR is toporese and the theorements the spectrum of CPR and the contrast of the CPR is toporese and definition of the CPR is toporese and the contrast definition of the CPR is toporese and the contrast of the theorements of the CPR is toporese and the contrast of the contrast CPR and the contrast of the CPR is toporese and the contrast topores and the contrast of the contrast of the CPR is toporese and the contrast topores and the contrast of the contrast of the contrast topores and the contrast of the contrast of the contrast of the contrast of the contrast topores and the contrast topores and the contrast of the co

ramopertubility²⁷ of many current CPR appertunes may be limited. Clinical prediction rules use outmore measures to determine the effeciveness of the intervention. Outcome measures must have a single operational identition²⁸ and require encouple respontiveness to truth current and the single hange in the condition²⁸ in addition, here measures should have a well contracted curved incom²⁸ and the collected

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Enthusiasm for prescriptive clinical prediction rules (eg, back pain and more): a quick word of caution

Robin Haskins,¹ Chad Cook²

on rules. (ab CPRs use baseline criteria called treat-

INTRODUCTION Preceippre clinical prediction rules (TER) are commony used in rubbin DSSMIAM 2010/COMES DURING WALDATION have noced concern about the viabations of these areas and the violations of these areas and the compared to the content reatment, placko, have been outlined involving modelling etch. Changing the comparator in a viabation etch on the violation who will get the drawn of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the drawn outcomes of the violation who will get the ate) best

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of CPR

Pros of Clinical Prediction Rules

It is a Sophisticated method to **Pattern Results**

- Clinical reasoning and treatment decision making methods used by clinicians are highly complex and decisions are rarely based on a *single* parameter (Boyd, 2011; Kassirer, 2010).
- CPR's cluster multiple parameters

Boyd GW. Education debate: clinical diagnostic reasoning. Intern Med J 2011;41:573-6. Kassirer JP. Teaching clinical reasoning: case-based and case coached. Acad Med 2010;85:1118-24.

Clinical Examples?

- SOB + Chest Pressure + Left Arm Pain =
- Elderly women + Fall + Inability to weight bear + ER deformity of the hip =
- LBP + Immobility + Fear + Inactivity =

Some Clinical prediction rules have clinical sensibility

- Pain during walking/standing, pain relief during sitting, bilateral leg pain, leg pain worse than back pain, older age = ?
- Unilateral OA, multi-plane hip ROM loss, weakness of the hip, duration of symptoms of < 1 year, reduced gait speed = ?

Cook et al. Physiother Research International. 2011 Wright et al. Phys Ther. 2011.

Clinical prediction rules have been used in clinical practice and have been effective

- Canadian C-Spine Rules
- Ottawa Ankle Rules
- Wells Criteria for DVT
- PERC score for reducing mortality

Gandara E, Wells PS. Clin Chest Med. 2010 Dec;31(4):629-39.

Good Clinical prediction rules typically outperform paternalistic care

- Paternalistic care
- Computerized decision typically beats the clinician, especially when the outcome is complex
- *Not you*? That's paternalistic thinking!

Ruland et al. J Am Med Inform Assoc. 2010 Jul-Aug;17(4):403-10.

J Occup Rehabil DOI 10.1007/s10926-013-9430-4

Development of a Computer-Based Clinical Decision Support Tool for Selecting Appropriate Rehabilitation Interventions for Injured Workers

Douglas P. Gross - Jing Zhang - Ivan Steenstra -Susan Barnoley - Calvin Haws - Tyler Amell -Greg McIntosh - Juliette Cooper - Osmar Zaiane

• Baseline clinician classification accuracy was high (ROC = 0.86) for selecting programs that lead to successful return-to-work. Classification performance for machine learning techniques outperformed the clinician baseline classification (ROC = 0.94).

Gross et al. J Occup Rehabil. 2013 Mar 7. [Epub ahead of print]

Cons of Clinical Prediction Rules

Most CPRs are Derivation Only

- Development of the rule—establishing the independent and combined effect of explanatory variables (or clinical predictors), which can be symptoms, signs, or diagnostic tests
- Generated through some form of regression analysis

(Reminder) All derived prescriptive rules are a reflection of treatment effect

- May be prognostic
- May be reflective of a bogus outcome measure
- May be spurious (Left Hip replacement)

Kamper SJ, Maher CG, Hancock MJ, Koes BW, Croft PR, Hay E. Best Pract Res Clin Rheumatol. 2010 Apr;24(2):181-91.

Sample is not Generalizable

- Inclusion criteria is too specific (18 to 60 but mean in the low thirties, ODI >20)
- Population is dissimilar to clinical population routinely seen



More?

- Most use tools that have low inter-rater reliability
- Most do not report accuracy
- Most have very wide confidence intervals
- Many are "so-what" studies

Haskins R, Rivett DA, Osmotherly PG. Clinical prediction rules in the physiotherapy management of low back pain: A systematic review. Man Ther 2011 Jun 3. [Epub ahead of print]

Sample Size is too Small

[RESEARCH REPORT]-

CHRISTINE A. IVERSON, PL DPT + THOMAS G. SUTLIVE, PL PHO, OCS¹ + MICHAEL S. CROWELL, PL DPT¹ REBECCAL, MOBBELL, PL DPT + MATTHEW IK PEXNIK, PL DPT + MATTHEW IK GARGER, PL DS/PL OCS, FAXOMPT¹ JOSEF N. MOORE, PL PHO, SCS, ARC¹ + ROBERT S. MAINTER, PL FAC, ECS, OCS, MAMPT¹

Lumbopelvic Manipulation for the Treatment of Patients With Patellofemoral Pain Syndrome: Development of a Clinical Prediction Rule

• N=49.....~27 variables

Regression Modeling with Small Sample Sizes is not Robust

 Predictive Modeling (CPRs) are exceptionally Fragile with Prescriptive Studies



Many Lack Clinical Sensibility

- Left hip for total hip replacement?
- Bilateral involvement for benefit of manipulation of the cervical spine
- Low back pain leads to poorer prognosis for shoulder disorders

Getting Published does not mean it is valid

- There are 3 million papers published each year, not all of them are good
- The "peer review" system has problems
- Self-serving cliques of reviewers, who are more likely to review each others' grant proposals and publications favorably
- · Some journals are fixated on these studies
- Journals need papers; they are more flexible

Lohsiriwat V, Lohsiriwat S. J Med Assoc Thai. 2007 Oct;90(10):2238-43.

The CPR Fails to Capture all Those who Benefit

- CPRs only capture a percentage of people who would benefit or would be diagnosed by the condition (tend to be <u>specific</u>, not sensitive)
- Thus, with a sensitivity of 63%, the Manip CPR captured 63 of the 100 subjects who benefitted from manipulation. 37% were missed by the CPR

CPRs are Used as clinical decision making models

- CPR's are NOT clinical decision making models
- CPR's represent a finding within the clinical decision making process
- CPRs are usually very specific and should be used in context with *other findings and near the end of the examination*

Prescriptive CPRs

- Prescriptive CPRs are more difficult to design and publish
- Are more difficult to find significance because the <u>outcome measure is</u> malleable (and different among studies)
- Frequently inappropriately derived (single arm studies), and the results are prognostic, versus prescriptive
- Bottom Line: There is trouble here.

Kent P, Hancock M, Petersen DH, Mjøsund HL. Clinimetrics corner: choosing appropriate study designs for particular questions about treatment subgroups. J Man Manip Ther. 2010 Sep;18(3):147-52.

The Outcome Measure is Malleable

- OMERACT-OARSI Criteria
- PASS (Patient Acceptable Symptom State)
- GRoC (change of 5)
- No Surgery (versus went to surgery)
- MCID's
- Results suggested that different "CPRs" were developed from same sample using different outcomes measures!!!

Wright A, et al. Predictors of response to physical therapy intervention in patients with primary hip osteoarthritis: a comparison of predictive modeling based on varying response criterion. IFOMPT Submission, 2012.

When Different Outcomes are									
Used									
Model	Variables	Individual P value	Coefficient T value	Model F value	Model Adjusted R ²	Model <i>P</i> value			
ODI Change Score	•Lower initial ODI •Met CPR •HEP compliance •Shorter duration sxs •Younger age	<0.01 0.04 0.07 0.01 <0.01	9.7 -2.1 -1.8 -2.5 -3.6	24.0	46.2	<i>P</i> <0.01			
NPRS Change Score	Lower initial NPRS Lower initial ODI Met CPR Shorter duration Sxs HEP compliance Diagnosis	<0.01 0.01 <0.01 <0.01 0.06 <0.01	14.9 -2.4 -3.5 -3.9 -1.8 -2.6	46.6	67	<i>P</i> <0.01			
Total Visits Rate of Recovery (0 to 100%)	• Met CPR • Lower initial NPRS • Met CPR • No irritability • Shorter duration Sxs	<0.01 0.09 0.01 0.03 <0.01	2.8 1.7 -2.6 2.3 -3.8	8.3	0.5	P<0.01 P<0.01			





- Different rules for different outcomes measures.
- Hope we pick the right one!!!

Different minimally important clinical difference (MCID) scores lead to different clinical prediction rules for the Oswestry disability index for the same sample of patients

Julie Schwind, Kenneth Learman, Bryan O'Halloran, Christopher Showalter, Chad Cook

Walsh University, North Canton, OH, USA

Different CPRs for different MCID's. Hope we pick the right one !!

Schwind et al. J Man Manip Ther. 2013;21:71-78.

When Different MCID's are Used								
Model	Variables	Individual P value	Odds Ratio (95% Confidence Interval)	Nagelkerke R ²	Model P value	% Correct		
ODI 50% Change (N=149)	Met CPR Younger Age Diagnosis	0.005 0.003 0.014	2.916 (1.380-6.163) 1.041 (1.014-1.069) 0.385(0.180-0.824)	0.231	0.000	57.0%		
ODI 30% Change (N=149)	Lower Baseline FABQ Shorter Symptom Duration Younger Age Diagnosis	0.044 0.012 0.001 0.012	1.039 (1.001-1.079) 1.008 (1.002-1.014) 1.054 (1.023-1.087) 0.337 (0.144-0.788)	0.214	0.000	70.5%		
ODI 17pt. Change (N=116)*	Lower Baseline ODI Shorter Symptom Duration Diagnosis Met CPR	0.010 0.064 0.063 0.007	0.954 (0.921-0.989) 1.009 (0.999-1.020) 0.441 (0.186-1.046) 3.387 (1.402-8.182)	0.245	0.000	48.3%		
ODI 10pt. Change (N=138) ^p	Lower Baseline ODI Younger Age Diagnosis	0.002 0.020 0.091	0.951 (0.921-0.981) 1.035 (1.005-1.065) 0.490 (0.215-1.120)	0.172	0.001	66.7%		
ODI 5pt. Change (N=144) ^s	Lower Baseline ODI Younger Age Diagnosis	0.008 0.043 0.082	0.956 (0.924-0.989) 1.034 (1.001-1.068) 0.442 (0.176-1.110)	0.139	0.006	79.2%		
ODI Final ≤ 20% (N=107) ⁴	Lower Baseline ODI Younger Age Shorter Symptom Duration Diagnosis Met CPR	0.000 0.002 0.083 0.061 0.029	1.113 (1.055-1.175) 1.064 (1.023-1.105) 1.009 (0.999-1.018) 0.366 (0.128-1.047) 3.288 (1.130-9.566)	0.491	0.000	56.1%		

Prescriptive Concerns

• Some (Beattie and Nelson 2006; Chaitow, 2010) have expressed concern regarding the indiscriminate use of CPRs and the potential undermining of clinical reasoning during the care of a patient.







Decision Making

- There are no situations in which one single decision point answers the care questions for the patient
- Decisions have multiple trigger or "fork" points.
- 1 CPR meets only 1 fork point





Thank You