

**Can AI improve
healthcare access,
quality, and
outcomes in the real
world? A hopeful
perspective.**

John Piette

School of Public Health

University of Michigan

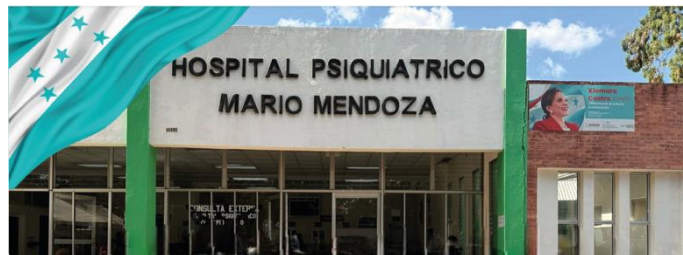
jpiette@umich.edu



Expertise in AI



Expertise in Psychology and Community Partners



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SAIL

**Symposium on Artificial Intelligence
for Learning Health Systems**

INTEGRATING AI INTO CLINICAL MEDICINE



**COMMENCEMENT SPEAKER
REPEATEDLY GETS BOOED BY UCF
STUDENTS AFTER SHE CALLS AI THE
'NEXT INDUSTRIAL REVOLUTION'**

[SWIPE FOR MORE]



Former Google CEO Eric Schmidt
Booed At University of Arizona While
Talking About AI; Reminds Grads
They Can Help Shape AI Future





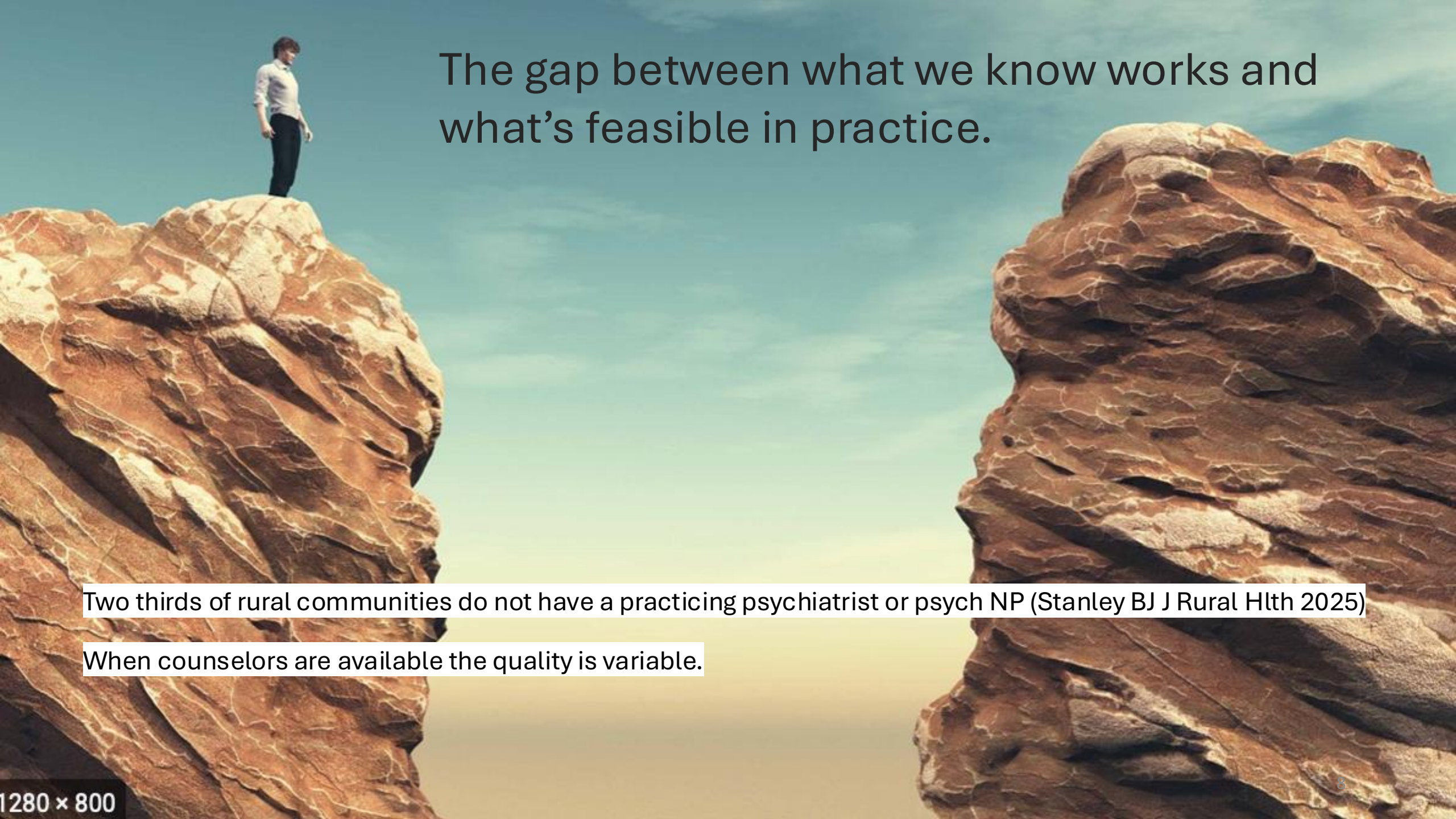
Types of Artificial Intelligence

Machine Learning

Reinforcement Learning

Natural Language Processing

RAG Systems

A person in a white shirt and dark pants stands on the edge of a large, reddish-brown rock formation. They are looking across a wide, deep gap towards another similar rock formation on the right. The sky is a clear, light blue. The overall scene conveys a sense of distance and challenge.

The gap between what we know works and what's feasible in practice.

Two thirds of rural communities do not have a practicing psychiatrist or psych NP (Stanley BJ J Rural Hlth 2025)

When counselors are available the quality is variable.

CBT works for a range of health problems

Hofmann, et al. The efficacy of cognitive behavioral therapy: A review of meta-analyses." *Cog Ther and Res* 36 (2012).





Sobre el Programa ▾

Facilitadores ▾

Líderes Comunitarios ▾

Participantes ▾

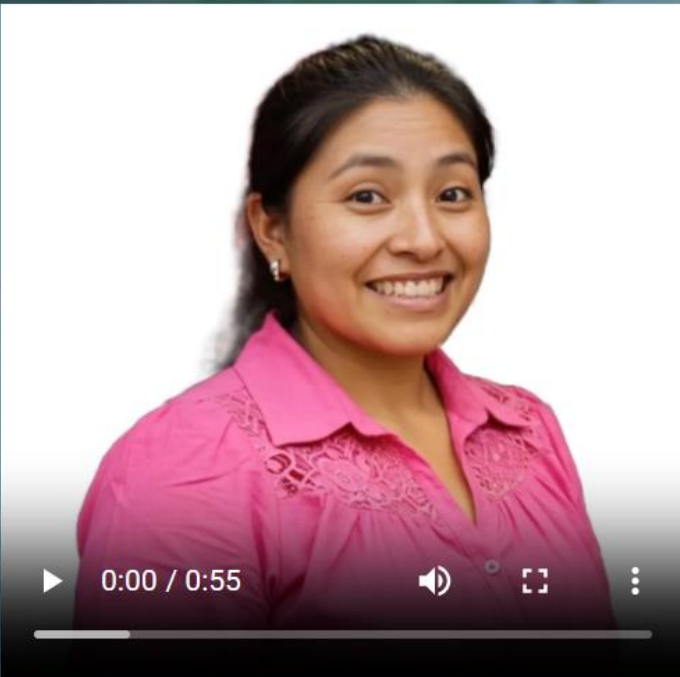
Investigación

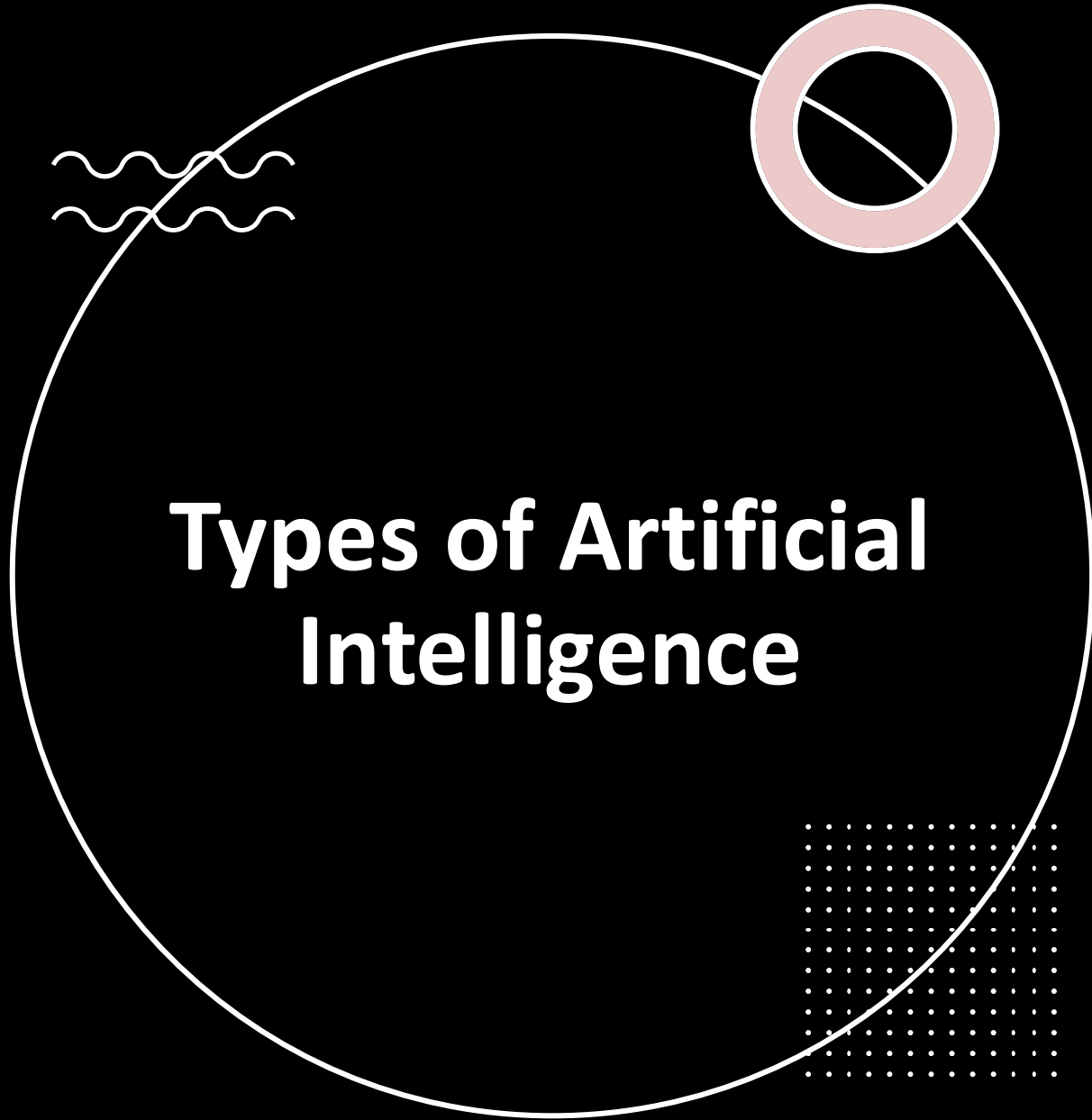
Contacto

Bienvenidos a Rompiendo Fronteras un espacio de Bienestar emocional para todos

Un programa práctico y accesible para enfrentar la ansiedad, la depresión y los conflictos personales. Aprende a cuidar tu salud mental y la de tu comunidad con estrategias efectivas y fáciles de aplicar.

[¿Qué es Rompiendo Fronteras?](#)





Machine Learning



Toad or Tree?



**Chihuahua or
Muffin?**

Suicide risk or normal teen angst?



Assari S. Combined racial and gender differences in the long-term predictive role of education on depressive symptoms and chronic medical conditions. *Journal of racial and ethnic health disparities*. 2017 Jun;4(3):385-96.



Types of Artificial Intelligence

Machine Learning

Reinforcement Learning

Patient barriers include

Transportation
Health and mobility
problems
Scheduling
Stigma

Typical CBT Program for Chronic Pain

System barriers include

Scarcity of therapist
Challenges of supervision
Cost and competing
demands

Session 1: Rationale for Treatment

Session 2: Stretching

Session 3: Exercise

Session 4: Breathing

Session 5: Relaxation

Session 6: Unhelpful Thoughts

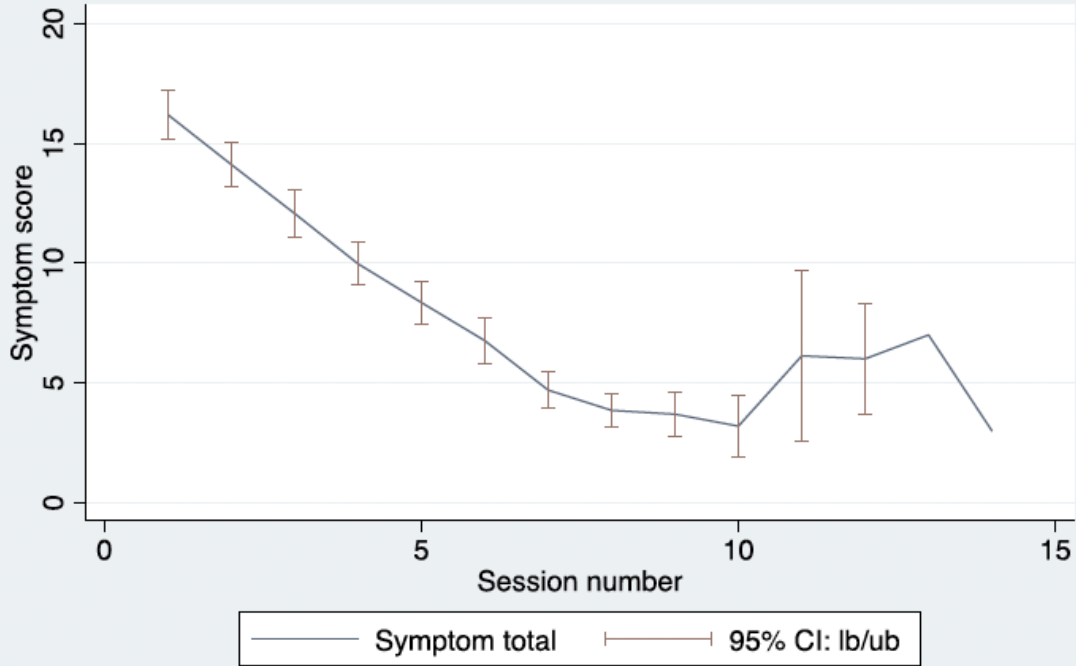
Session 7: Unhelpful Thoughts (continued)

Session 8: Time-Based Activity Pacing

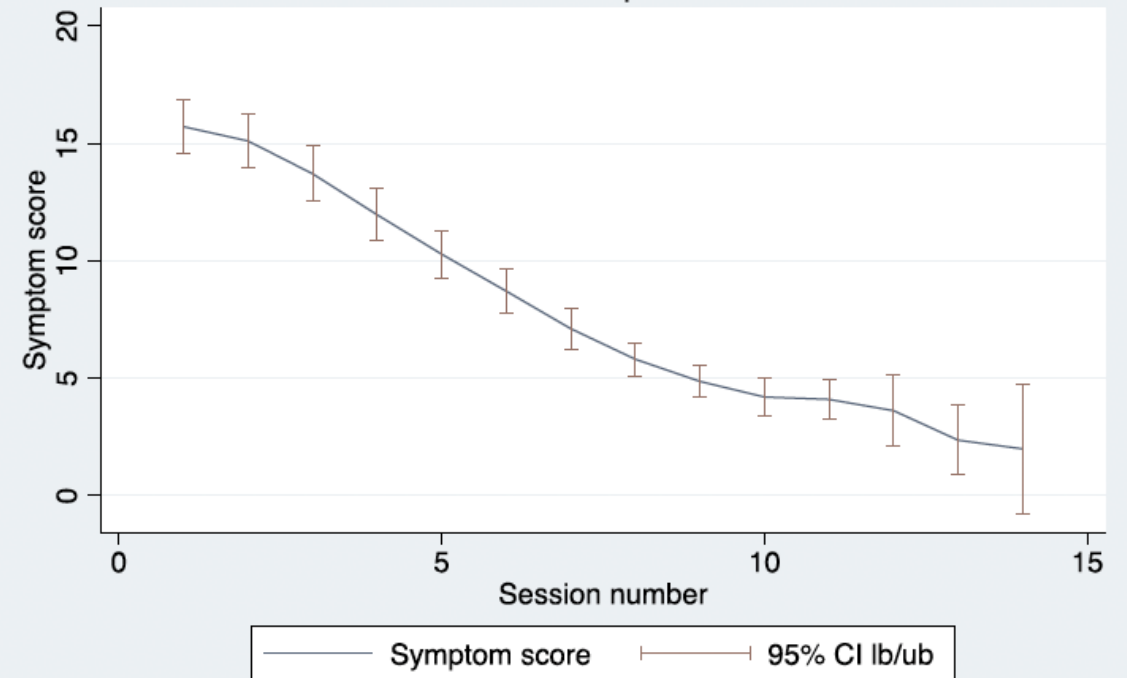
Session 9: Sleep Skills

Session 10: Relapse Prevention

Average Symptom Score by Session
Thailand



Average Symptom Score by Session
Iraq



Murray LK, et al. Understanding mechanisms of change: An unpacking study of the evidence-based common-elements treatment approach (CETA) in low and middle income countries. Behaviour research and therapy. 2020 Jul 1;130:103430.

MacLean RR, et al. Using daily ratings to examine treatment dose and response in cognitive behavioral therapy for chronic pain: A secondary analysis of the co-operative pain education and self-management clinical trial. Pain Med 2023 Jul 1;24(7):846-54.

Reinforcement Learning

RL is a process of learning from repeated interactions with a partially known and stochastic environment

RL seeks to maximize a numerical value that represents that benefit for a given user and the overall population.



3 action choices



reward score:
{steps+pain level}



45 minute live



15 minute live



Digital communication

Outcomes as good as standard care.....

....less than half the therapist time.

Piette JD, et al. Artificial Intelligence (AI) to improve chronic pain care: Evidence of AI learning. Intelligence-Based Med. 2022.

Piette JD. Cognitive behavioral therapy for chronic pain supported by digital patient feedback and artificial intelligence: do patients with socioeconomic risk factors benefit?. Int-Based Med. 2024.

JAMA Internal Medicine | [Original Investigation](#) | [LESS IS MORE](#)

Patient-Centered Pain Care Using Artificial Intelligence and Mobile Health Tools

A Randomized Comparative Effectiveness Trial

John D. Piette, MSc, PhD; Sean Newman, MS; Sarah L. Krein, PhD; Nicolle Marinec, MPH; Jenny Chen, MPH; David A. Williams, PhD; Sara N. Edmond, PhD; Mary Driscoll, PhD; Kathryn M. LaChappelle, MPH; Robert D. Kerns, PhD; Marianna Maly, MA; H. Myra Kim, ScD; Karen B. Farris, PhD; Diana M. Higgins, PhD; Eugenia Buta, PhD; Alicia A. Heapy, PhD

IMPORTANCE Cognitive behavioral therapy for chronic pain (CBT-CP) is a safe and effective alternative to opioid analgesics. Because CBT-CP requires multiple sessions and therapists are scarce, many patients have limited access or fail to complete treatment.

OBJECTIVES To determine if a CBT-CP program that personalizes patient treatment using reinforcement learning, a field of artificial intelligence (AI), and interactive voice response (IVR) calls is noninferior to standard telephone CBT-CP and saves therapist time.

DESIGN, SETTING, AND PARTICIPANTS This was a randomized noninferiority, comparative effectiveness trial including 278 patients with chronic back pain from the Department of Veterans Affairs health system (recruitment and data collection from July 11, 2017-April 9, 2020). More patients were randomized to the AI-CBT-CP group than to the control (1.4:1) to maximize the system's ability to learn from patient interactions.

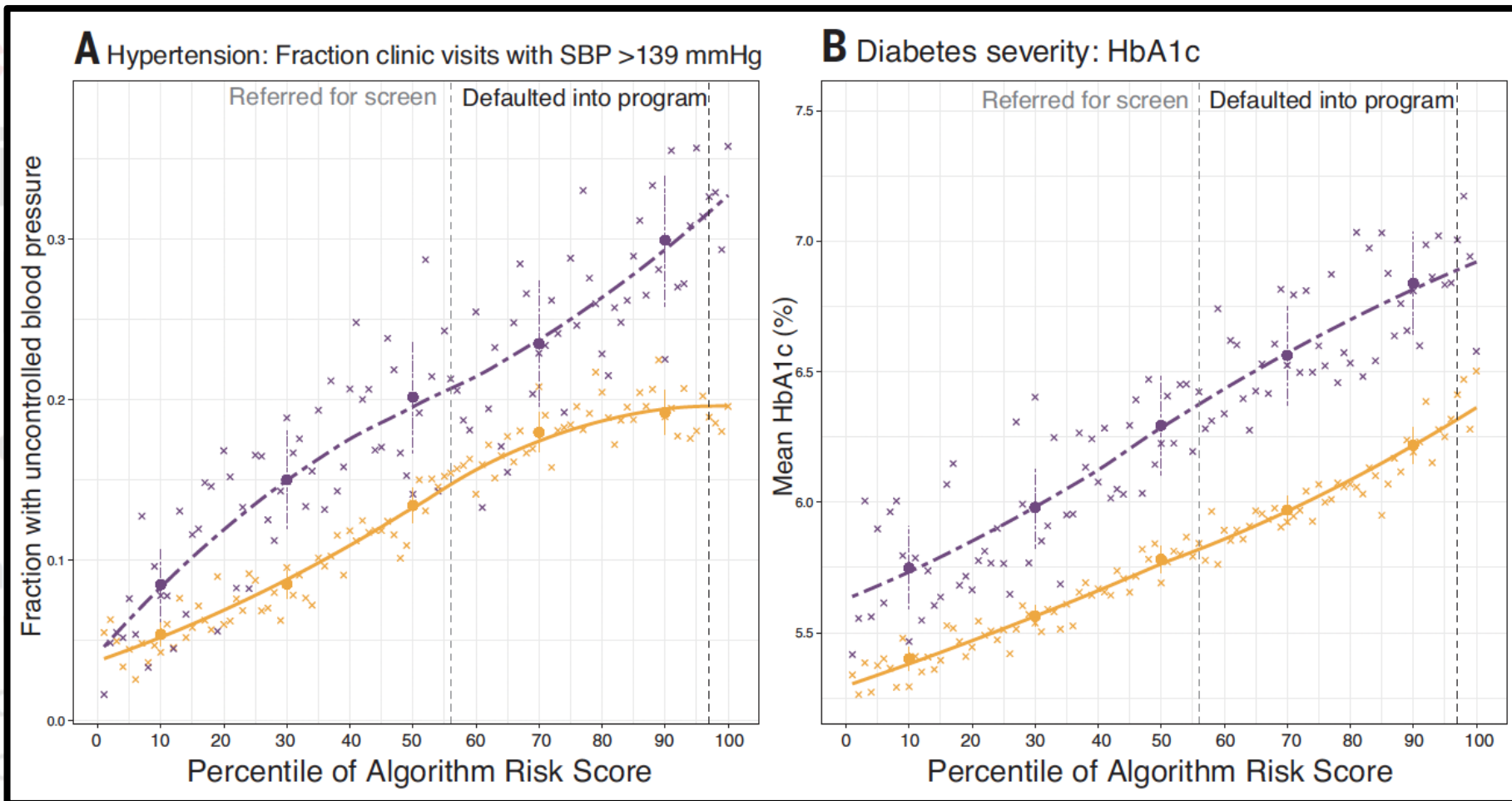
ECONOMICS

Dissecting racial bias in an algorithm used to manage the health of populations

Ziad Obermeyer^{1,2*}, Brian Powers³, Christine Vogeli⁴, Sendhil Mullainathan^{5*†}

Health systems rely on commercial prediction algorithms to identify and help patients with complex health needs. We show that a widely used algorithm, typical of this industry-wide approach and affecting millions of patients, exhibits significant racial bias: At a given risk score, Black patients are considerably sicker than White patients, as evidenced by signs of uncontrolled illnesses. Remedying this disparity would increase the percentage of Black patients receiving additional help from 17.7 to 46.5%. The bias arises because the algorithm predicts health care costs rather than illness, but unequal access to care means that we spend less money caring for Black patients²¹ than

RESEARCH ARTICLE



Remedying this disparity would increase the percentage of Black patients receiving additional help from 17.7 to 46.5%. The bias arises because the algorithm predicts health care costs rather than illness, but unequal access to care means that we spend less money caring for Black patients than

Counterfactually Fair Reinforcement Learning via Sequential Data Preprocessing

Jitao Wang^{1,a}, Chengchun Shi^{2,b}, John D. Piette^{3,c},
John R. Loftus^{2,d}, Donglin Zeng^{1,e}, Zhenke Wu^{1,f}

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²Department of Statistics, London School of Economics, UK

³Department of Health Behavior and Health Equity,
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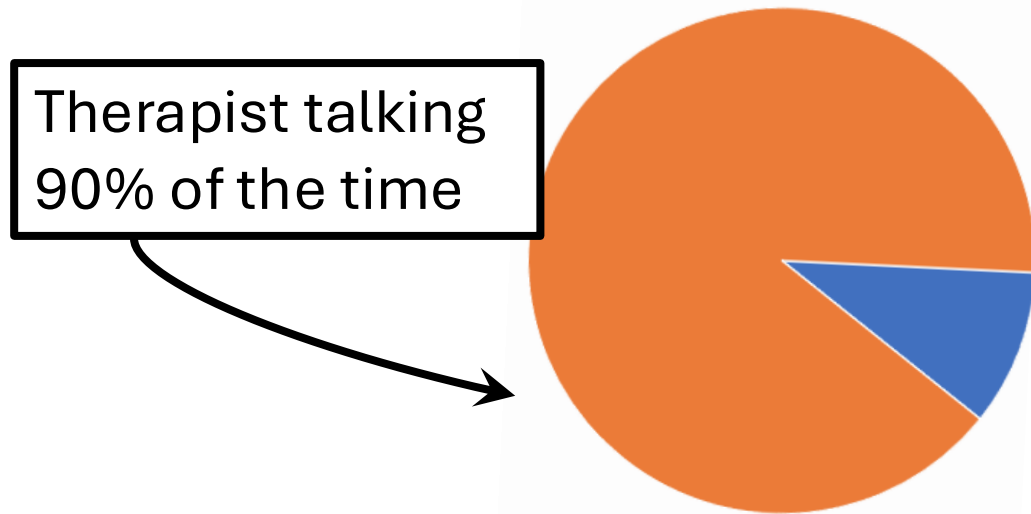
Types of Artificial Intelligence

Machine Learning

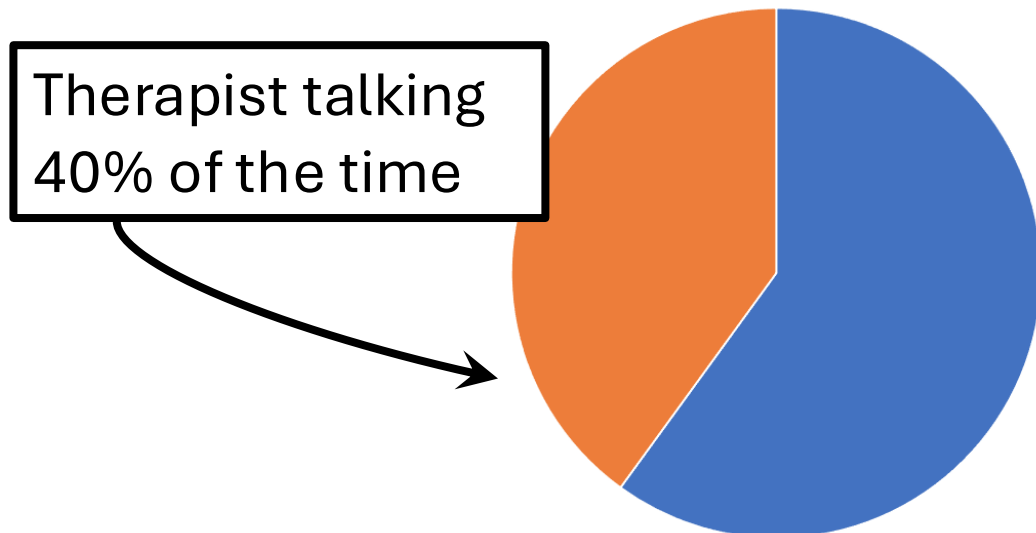
Reinforcement Learning

Natural Language Processing

Clinician-dominated interaction (bad):



More egalitarian interaction (better):



What Makes a Good Counselor? Learning to Distinguish between High-quality and Low-quality Counseling Conversations

Verónica Pérez-Rosas¹, Xinyi Wu¹, Kenneth Resnicow², Rada Mihalcea¹

¹Computer Science & Engineering, University of Michigan, USA

²School of Public Health, University of Michigan, USA

{vrncapr, wuxinyi, kresnic, mihalcea}@umich.edu

Abstract

The quality of a counseling intervention relies highly on the active collaboration between clients and counselors. In this paper, we explore several linguistic aspects of the collaboration process occurring during counseling

we explore which aspects of the collaboration process occurring between counseling participants are related to counseling quality. Our categorization of counseling quality relies on general counseling principles taken from the literature on client-centered counseling (Miller and Rollnick, 2013).

The Motivational Interviewing (MI) Spirit

Respect

Empathy

Hope



Acceptance

Patience

Collaboration

MI Treatment Integrity (MITI) Scoring: Global Dimensions

Cultivating Change Talk

Low		High		
1	2	3	4	5
Clinician shows no explicit attention to, or preference for, the client's language in favor of changing	Clinician sporadically attends to client language in favor of change – frequently misses opportunities to encourage change talk	Clinician often attends to the client's language in favor of change, but misses some opportunities to encourage change talk	Clinician consistently attends to the client's language about change and makes efforts to encourage it	Clinician shows a marked and consistent effort to increase the depth, strength, or momentum of the client's language in favor of change

Partnership

Low		High		
1	2	3	4	5
Clinician actively assumes the expert role for the majority of the interaction with the client. Collaboration or partnership is absent.	Clinician superficially responds to opportunities to collaborate.	Clinician incorporates client's contributions but does so in a lukewarm or erratic fashion.	Clinician fosters collaboration and power sharing so that client's contributions impact the session in ways that they otherwise would not.	Clinician actively fosters and encourages power sharing in the interaction in such a way that client's contributions substantially influence the nature of the session.

Softening Sustain Talk

Low		High		
1	2	3	4	5
Clinician consistently responds to the client's language in a manner that facilitates the frequency or depth of arguments in favor of the status quo.	Clinician usually chooses to explore, focus on, or respond to the client's language in favor of the status quo.	Clinician gives preference to the client's language in favor of the status quo, but may show some instances of shifting the focus away from sustain talk.	Clinician typically avoids an emphasis on client language favoring the status quo.	Clinician shows a marked and consistent effort to decrease the depth, strength, or momentum of the clients language in favor of the status quo.

Empathy

Low		High		
1	2	3	4	5
Clinician gives little or no attention to the client's perspective.	Clinician makes sporadic efforts to explore the client's perspective. Clinician's understanding may be inaccurate or may detract from the client's true meaning.	Clinician is actively trying to understand the client's perspective, with modest success.	Clinician makes active and repeated efforts to understand the client's point of view. Shows evidence of accurate understanding of the client's worldview, although mostly limited to explicit content.	Clinician shows evidence of deep understanding of client's point of view, not just for what has been explicitly stated but what the client means but has not yet said.

MI Treatment Integrity (MITI) Coding System

MI-Adherent Behaviors

- Seeking Collaboration
- Reflections
- Emphasizing Autonomy
- Affirmations
- Open Questions

MI Non-Adherent Behaviors

Persuading: Overt attempts to change opinions using logic or arguments; Giving unsolicited advice or solutions

Confronting: Direct disagreement or challenging

Original Paper

Development and Evaluation of ClientBot: Patient-Like Conversational Agent to Train Basic Counseling Skills

Michael J Tanana¹, PhD; Christina S Soma², MEd; Vivek Srikumar³, PhD; David C Atkins⁴, PhD; Zac E Imel², PhD

¹Social Research Institute, College of Social Work, University of Utah, Salt Lake City, UT, United States

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³School of Computing, University of Utah, Salt Lake City, UT, United States

⁴Psychiatry and Behavioral Science, University of Washington, Seattle, UT, United States

Original Paper

Development and Evaluation of ClientBot: Patient-Like

“Participants in ClientBot used 91% more reflections during practice with feedback and 76% more reflections after feedback was removed relative to the control group....”

Michael J Tanana¹, PhD, Christina S Soma², MEd, Vivek Sikumar³, PhD, David C Atkins⁴, PhD, Zac E Inel¹, PhD

¹Social Research Institute, College of Social Work, University of Utah, Salt Lake City, UT, United States

²College of Education, University of Utah, Salt Lake City, UT, United States

³School of Computing, University of Utah, Salt Lake City, UT, United States

⁴Psychiatry and Behavioral Science, University of Washington, Seattle, UT, United States



Training on expert-labeled data

ANNO-MI: A DATASET OF EXPERT-ANNOTATED COUNSELLING DIALOGUES

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Rim Helaoui¹, Ehud Reiter³, Diego Reforgiato Recupero², Daniele Riboni²*

¹Philips Research, Eindhoven, Netherlands

²Department of Mathematics & Computer Science, University of Cagliari, Cagliari, Italy

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ABSTRACT

Research on natural language processing for counselling dialogue analysis has seen substantial development in recent years, but access to this area remains extremely limited due to the lack of publicly available expert-annotated therapy conversations. In this work, we introduce *AnnoMI*, the first publicly and freely accessible dataset of professionally transcribed and expert-annotated therapy dialogues. It consists of 133 conversations that demonstrate high- and low-quality motivational interviewing (MI), an effective counselling technique, and the annotations by domain experts cover key MI attributes. We detail the data collection process including dialogue selection, transcription and annotation. We also present analyses of *AnnoMI* and discuss its potential applications.

[11] and deep learning methods [12, 13, 14, 15] have both been leveraged to predict MI codes and aspects such as therapist empathy. More recently, Pérez-Rosas et al. [16] released a dataset of high- & low-quality-MI² dialogues taken from online video-sharing platforms and analysed the linguistic aspects that distinguish between MI-adherent and non-adherent therapy. On the other hand, Wu et al. [17, 18] explored predicting therapist empathy in low-resource settings.

Despite its progress, MI-related natural language processing (NLP) has been limited by the lack of publicly available MI conversations due to privacy constraints. Most work has been based on undisclosed corpora of MI dialogues and annotations, making it difficult to reproduce and build on previous findings. To the best of our knowledge, the only publicly and freely accessible MI corpus is from [16], based

Examining Spanish Counseling with MIDAS: a Motivational Interviewing Dataset in Spanish

Aylin Gunal^{*†} Bowen Yi^{*†} John Piette[†] Rada Mihalcea[†] Verónica Pérez-Rosas[‡]

[†] University of Michigan, Ann Arbor

[‡] Texas State University, San Marcos

{gunala, bowenyi, jpiette, mihalcea}@umich.edu, vperezr@txstate.edu

Abstract

Cultural and language factors significantly influence counseling, but Natural Language Processing research has not yet examined whether the findings of conversational analysis for counseling conducted in English apply to other languages. This paper presents a first step towards this direction. We introduce MIDAS (Motivational Interviewing Dataset in Spanish), a counseling dataset created from public video

in clinical psychotherapy have shown that cultural differences between patients and providers can lead to disparities in quality of mental health care due to unsuccessful interactions (Oh and Lee, 2016). This highlights the importance of collecting and using culturally diverse counseling datasets when developing NLP-based tools that support counseling practice.

In this study, we introduce MIDAS (Motivational Interviewing Dataset in Spanish) a

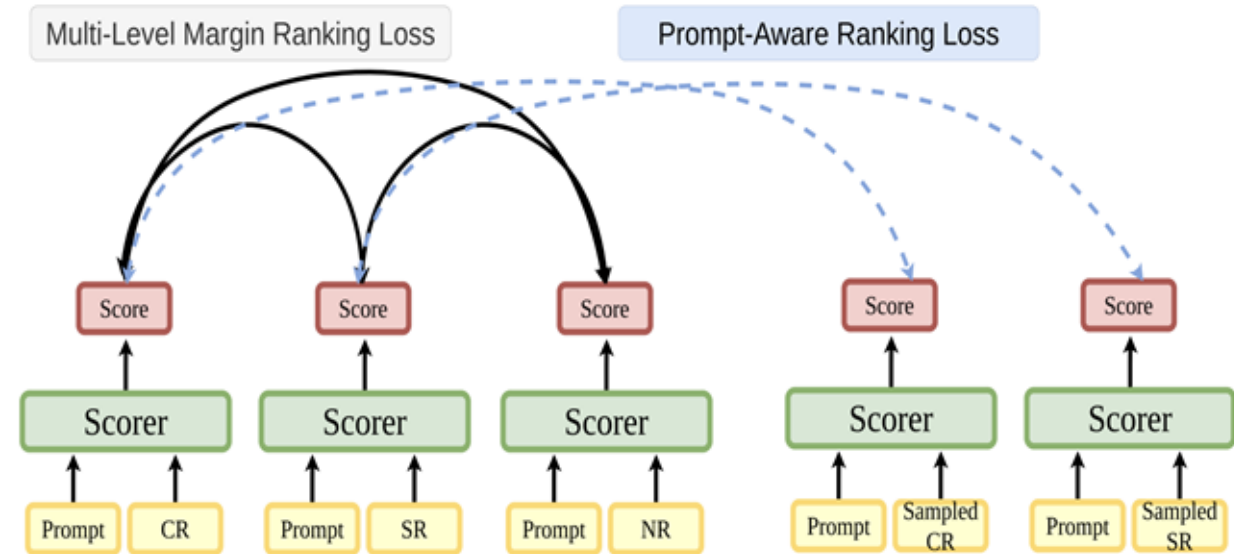


An AI-support Tool for Improving the Quality of Behavior Change Counseling in Latin America

PAIR: Prompt-Aware margin Ranking for Counselor Reflection Scoring in Motivational Interviewing

Do June Min, Veronica Perez-Rosas, Kenneth Resnicow, and Rada Mihalcea

Proceedings of the 2022 Confer on Empirical Methods in Natural Language Processing, pages 148–158



We developed a supervised learning-to-rank model to evaluate MI reflections using a corpus of 2,544 prompt–response pairs for 318 patient training prompts.’

MI Assignment Week 3

Disclaimer

Please note that as part of our natural language processing (NLP) project, we will collect data from your submissions. We will save your responses, your assignment scores, and any feedback you might give us. Your data will be stored in a secure server owned by our team. Your personal information such as your name or UMID will not be associated with your submissions, will only be used to distinguish authorship of submissions.

Instructions

Please write at least one reflection for each of the prompts below. You can save your progress using the 'Save' button at the end of the page. To resume your work with saved responses, type your UMID and click the 'Load' button at the end of the page. Once you have completed your assignment each of your responses will be automatically scored by our system.

When you are finished with the assignment, press the 'Submit' button at the end of the page to submit your responses. Please note that there might be a latency of 5~10 seconds for the model to process your responses.

For each prompt, you can submit up to 2 responses using the two input fields provided.

Prompt 1: I have no energy. The thought of working out now is out of the question. I used to bike and play tennis but that seems a lifetime ago. I would love to feel alive again, but I am just so tired all the time.

Response #1: You miss your old self when you were so active but now you wonder if you can ever regain that type of energy.

Your Score: 0.92

Suggested Response 1: Getting back to regular physical activity is really appealing to you but also seems a bit out of reach. You're excited to get back to a place where you feel invigorated again.

Suggested Response 2: You used to bike and play tennis but that seems a bit outside your reach right now. If you could find a way to be active that wasn't super draining, it might be something you'd try.

Prompt 1: I have no energy. The thought of working out now is out of the question. I used to bike and play tennis but that seems a lifetime ago. I would love to feel alive again, but I am just so tired all the time.

Response #2: Have you tried other types of sports like maybe swimming? That's a lot easier on your joints.

Your Score: 0.15

Michigan

Instrucciones

A continuación se muestran varios escenarios de psicoterapia en los que practicarás el uso de escucha reflexiva. Por cada situación personal de un paciente, escribe al menos una respuesta que demuestre el uso de la técnica de escucha reflexiva. Para guardar tu progreso, presiona el botón "Guardar". Para reanudar tu trabajo, ingresa tu usuario y haz clic en el botón 'Cargar' al final de la página. Una vez que hayas respondido todos los ejercicios da clic en el botón "Enviar" al final de la página. El sistema calificará tus respuestas de forma automática. Ten en cuenta que puede haber una latencia de 5 a 10 segundos al procesar tus respuestas.

Usuario. Si es la primera vez que usas el sistema, elige un nombre de usuario, de otra forma, escribe tu nombre de usuario. Nota: usa el nombre de usuario que te fue asignado.

Descargo de responsabilidad


Las respuestas, puntuaciones de cada ejercicio y comentarios colectados por esta herramienta serán almacenadas en un servidor seguro propiedad de la Universidad de Michigan. Nuestro sistema no almacena información personal. La información colectada en este estudio será utilizada solo de forma agregada.

Si sale o recarga la página, sus cambios podrían perderse. Asegúrese de hacer clic en el botón Guardar o Enviar al final de la página.

Deployment in Honduras




50 Participants: recruited from a *major psychiatric hospital and community service organizations* in Honduras.

 Two attempts on **AI scoring system** before coaching session



Human expert coaching session



 Two Attempts on **AI scoring system** after coaching session



MI psychologist.

Qualitative Examples

PROMPT: Por supuesto, me gustaría perder peso. Pero odio las dietas. Las he probado todas. Cada vez me siento privado y tengo hambre. Luego comienzo a sentirme resentido.

RESPONSE: Cada cuerpo es diferente, puede que su cuerpo se sacie de forma diferente a la de los demás, por lo cual es necesario el apoyo de un profesional en este campo, considerarías tener este apoyo?

SCORE: 0.08

English Translation:

PROMPT: *Of course I'd like to lose weight. But I hate diets. I've tried them all. Every time I feel deprived and hungry. Then I start feeling resentful.*

RESPONSE: *Everybody is different; your body may feel full differently than others, so professional support is necessary. Would you consider getting that support?*

PROMPT: Tengo pánico de empezar con la insulina. No puedo lidiar con las agujas, la sangre, la constante preocupación por mi azúcar. Siempre esperé poder controlar esto sin insulina.

RESPONSE: La idea de usar insulina te provoca mucho miedo, sobre todo por las agujas, la sangre y la sensación de estar en vigilancia constante.

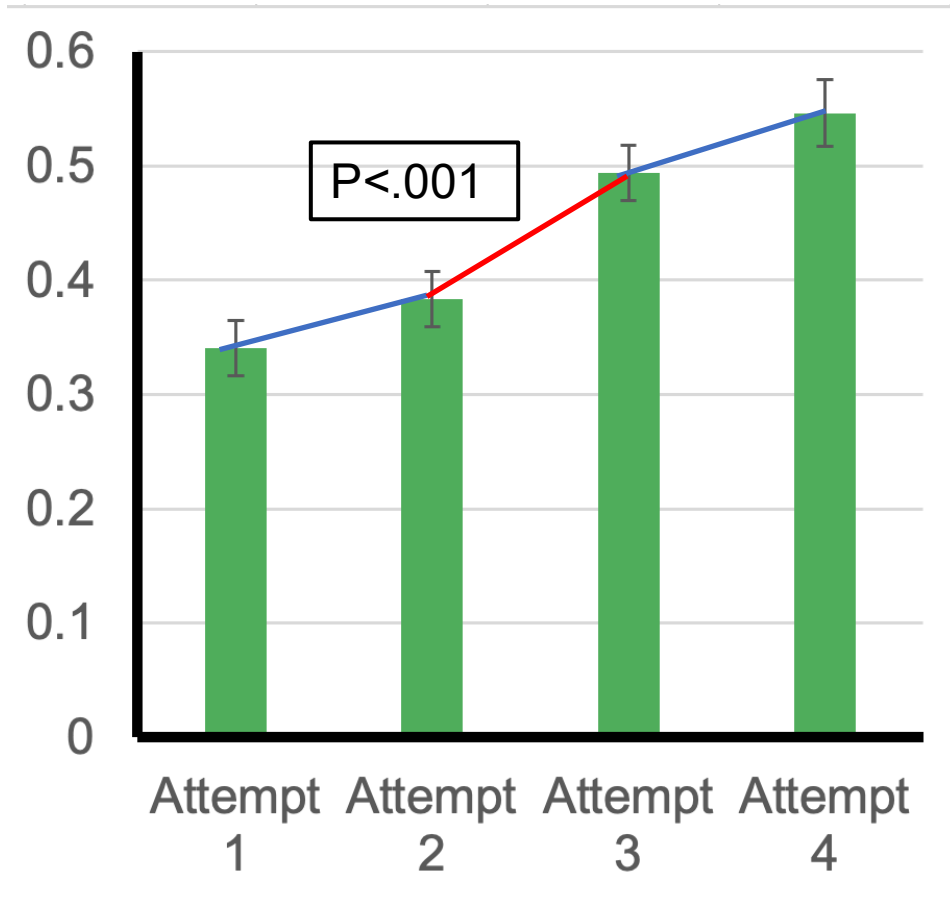
SCORE: 0.940

English Translation:

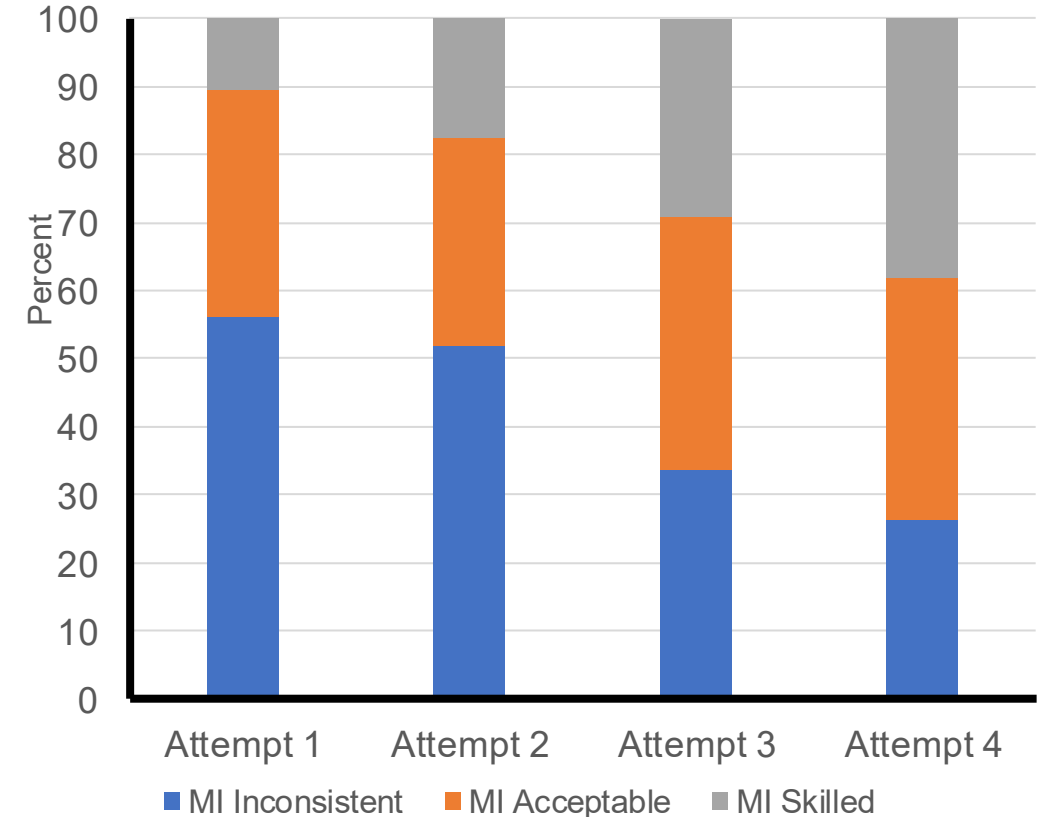
PROMPT: *I'm panicked about starting insulin. I can't deal with needles, blood, and the constant worry about my sugar levels. I always hoped I could manage this without insulin.*

RESPONSE: *The idea of using insulin brings up a lot of fear for you, especially because of the needles, the blood, and the feeling of being under constant monitoring.*

Assessing the AI Tool Effectiveness



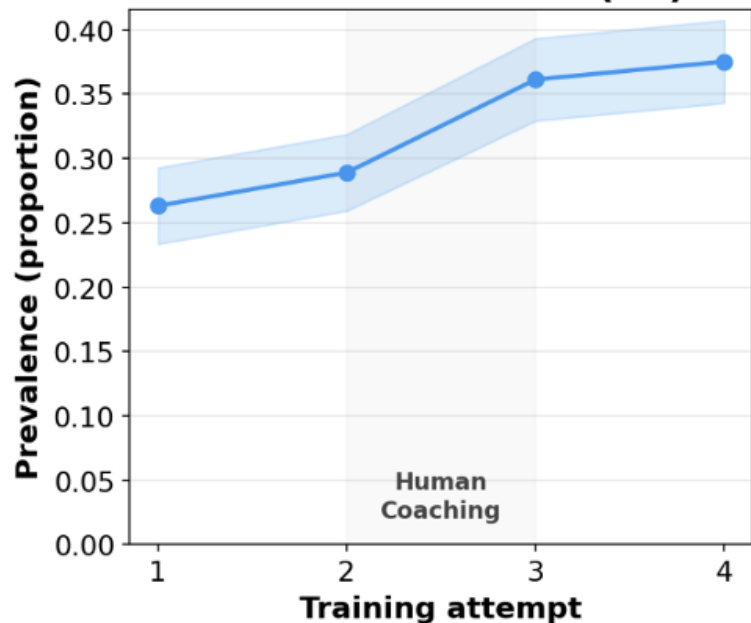
Mean reflection scores increased steadily from Attempt 1 to Attempt 4.



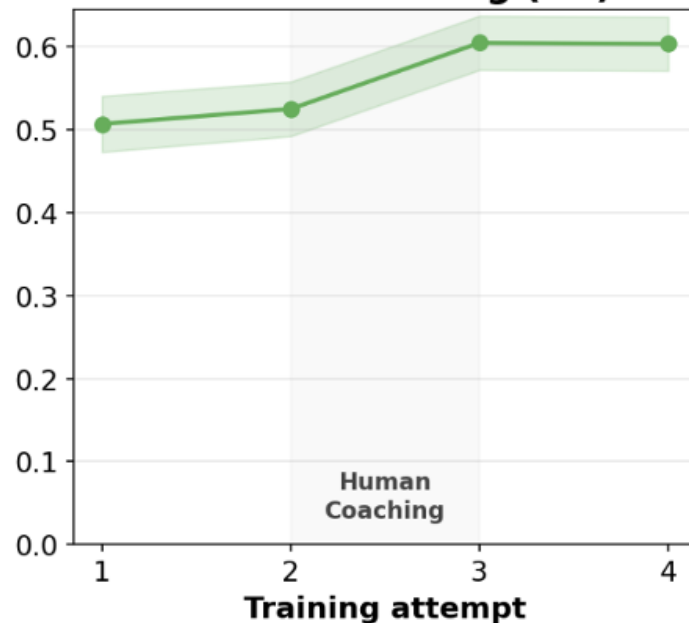
High-quality reflections increased from 10% at the first attempt to 38% at the fourth, while low-quality responses decreased from 56% to 26% ($p < .001$).

CR behaviors ↑

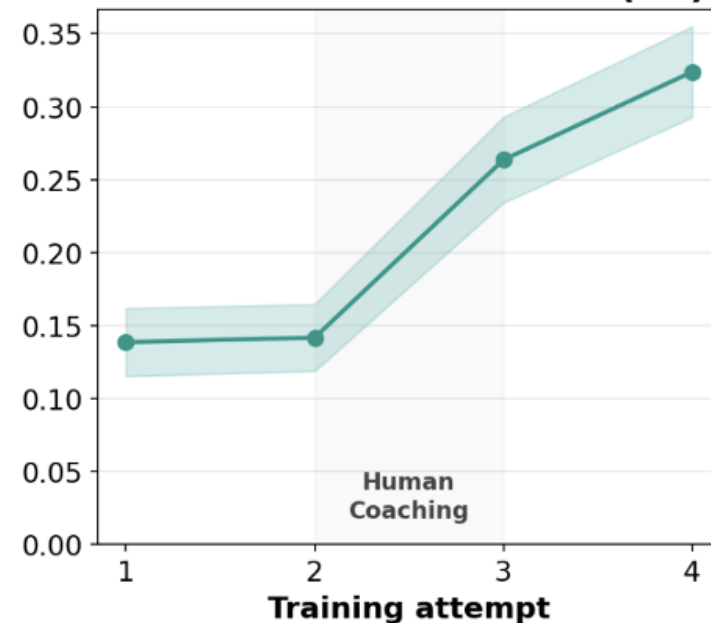
Emotion Reflection (CR)



Inferred Meaning (CR)

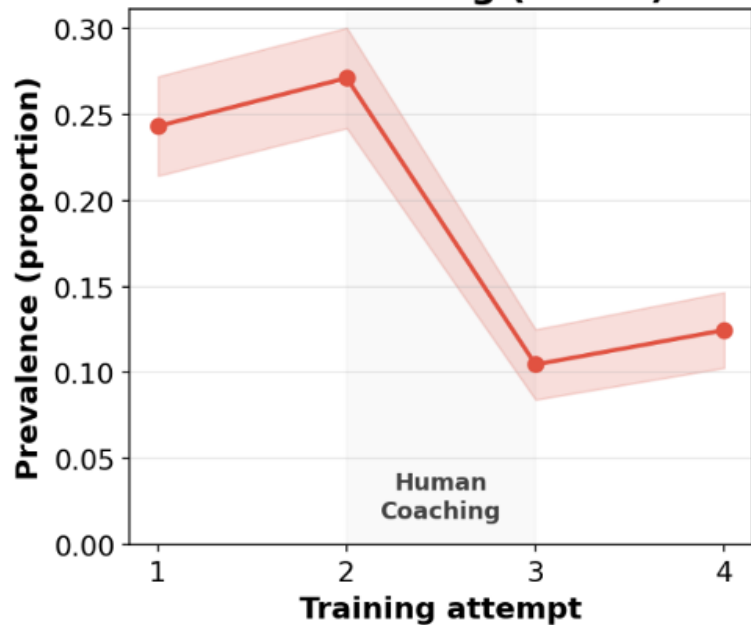


Double-Sided Reflection (CR)

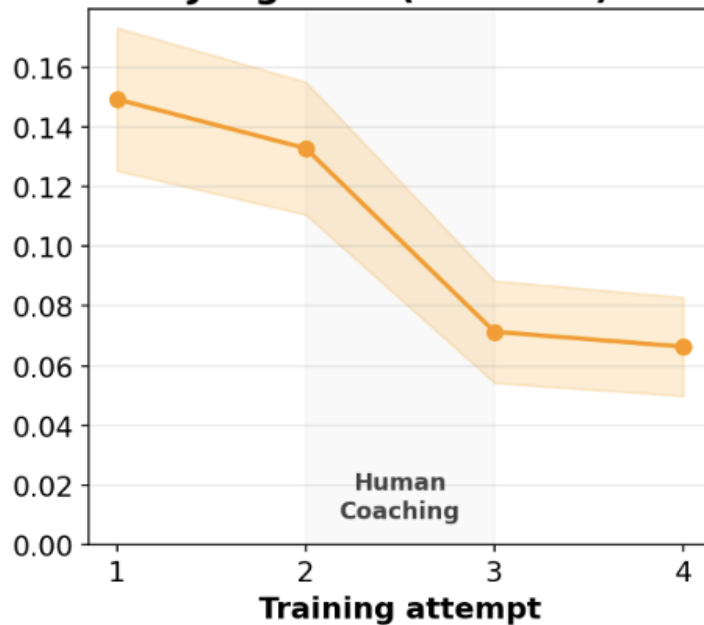


Non-adherent ↓

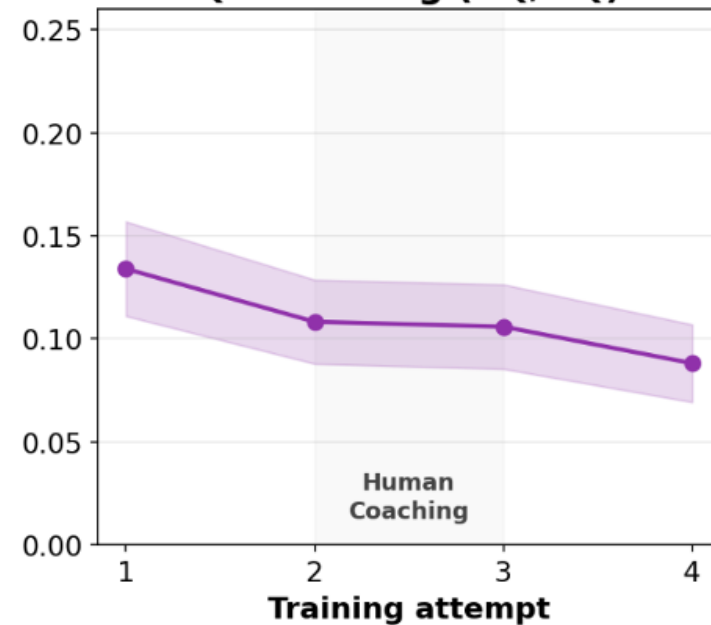
Advice-Giving (Direct)



Judgment (Confront)



Questioning (CQ/OQ)



Training a roBERTa classifier for a broader range of MI behaviors



Expert Annotated Transcripts

Clinician: Thanks for coming in today, Jake. I see from your intake form that you wanted to talk about some health questions related to being sexually active. Can you tell me a bit about what's on your mind?

Client: Yeah, um, well... my mom said I should talk to a doctor about this stuff. I mean, I know about protection and everything, but sometimes my girlfriend and I don't use anything.

Clinician: So you're aware of protection options, but there are times when you and your girlfriend don't use them. What's that like for you?

Client: I guess it worries me sometimes. Like, I know pregnancy or getting an STD would be really bad. But it's just... I don't know, it's awkward to bring up with her, you know?

Clinician: It sounds like part of you recognizes the real risks - pregnancy and STDs - and you're concerned about those. At the same time, there's this awkwardness about discussing it with your girlfriend that makes it challenging.

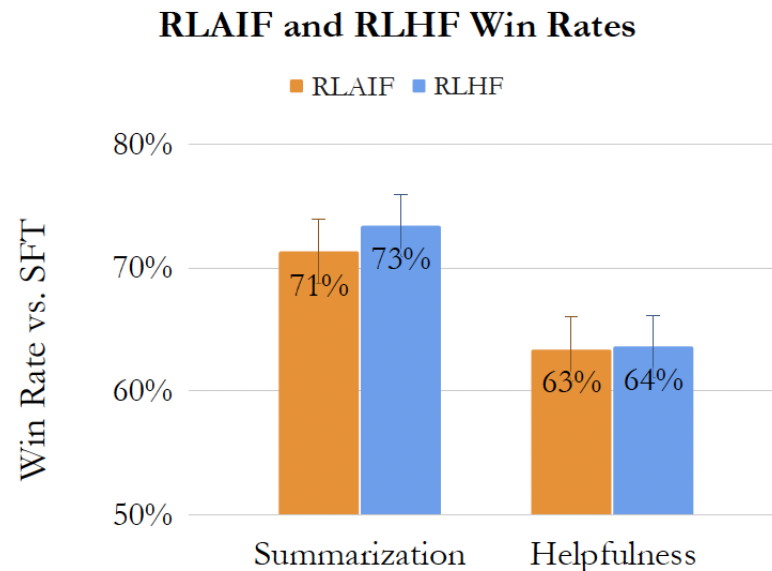
Client: Exactly. And honestly, we're pretty careful most of the time. It's not like we never use protection. Just sometimes in the moment, you know?

RLAIF vs. RLHF: Scaling Reinforcement Learning from Human Feedback with AI Feedback

Harrison Lee¹ Samrat Phatale¹ Hassan Mansoor¹ Thomas Mesnard¹ Johan Ferret¹ Kellie Lu²
Colton Bishop¹ Ethan Hall² Victor Carbune¹ Abhinav Rastogi¹ Sushant Prakash²

Abstract

Reinforcement learning from human feedback (RLHF) has proven effective in aligning large language models (LLMs) with human preferences, but gathering high-quality preference labels is expensive. RL from AI Feedback (RLAIF), introduced in Bai et al. (2022b), offers a promising alternative that trains the reward model (RM) on preferences generated by an off-the-shelf LLM. Across the tasks of summarization, helpful dialogue generation, and harmless dialogue generation, we show that RLAIF achieves comparable performance to RLHF. Furthermore, we take a



Harmless Rate by Policy

Emotion Detection
using
ROBERTa



Client: Man, it's rough out here. I've been trying to keep to myself mostly, you know? The shelter's okay sometimes, but I don't like being around all those people. Too many voices, too much noise. And those case managers keep bothering me about taking meds and stuff. I'm doing fine without all that.

Prompt: Which option do you like the best?

RL Feedback to boost quality

Prompt: Generate two possible affirmations





Types of Artificial Intelligence

Machine Learning

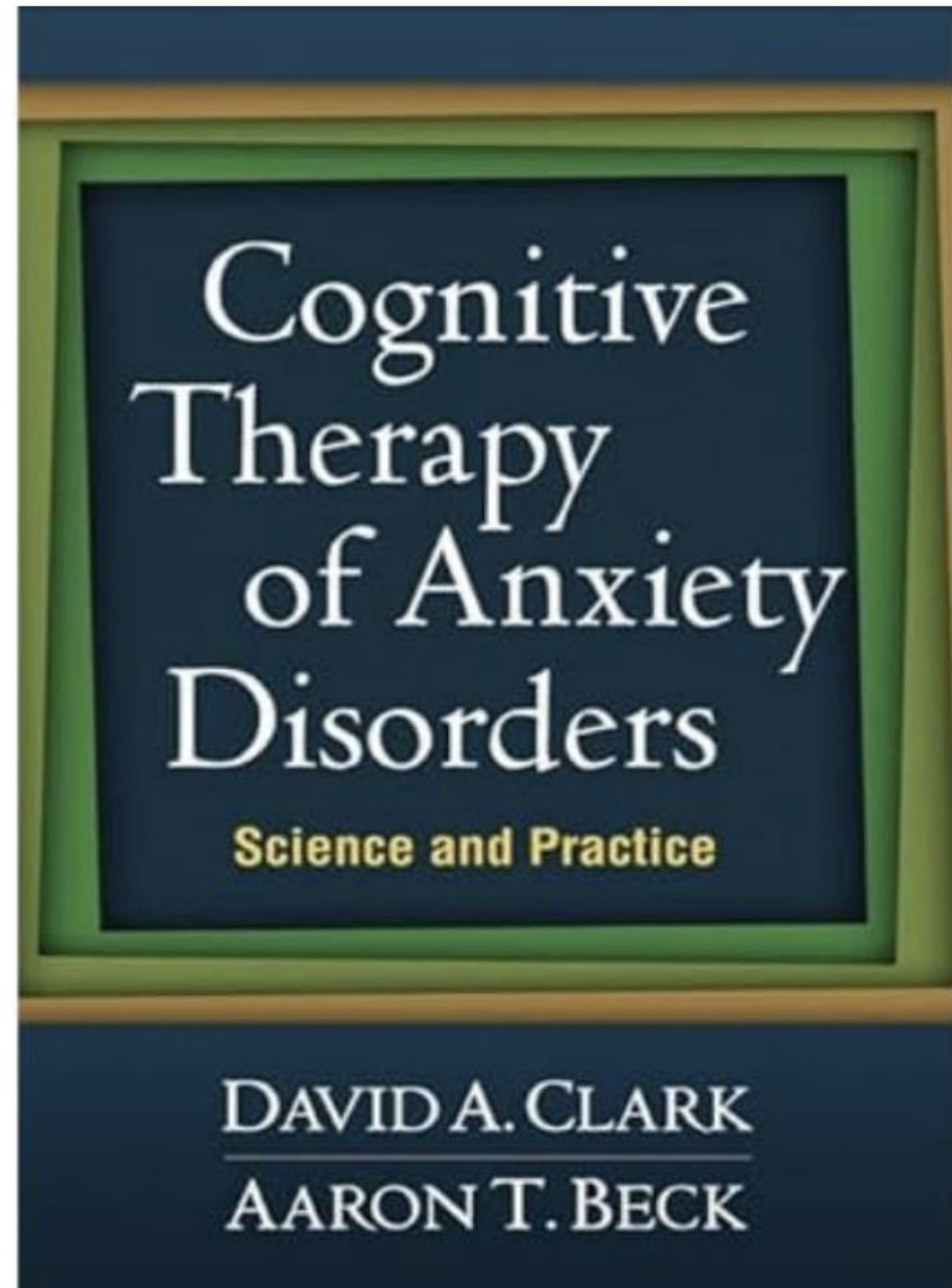
Reinforcement Learning

Natural Language Processing

RAG Systems

English version:
628 pages!

Spanish version:
994 pages!



How does RAG work?

Books on CBT and MI
Audios y videos from a CBT course
Expert-labeled transcripts
Guidelines
National policies
Available services

A few optimistic conclusions



Evidence-based, brief structured therapies are teachable and they work.

RL alone or with LLMs may improve access, efficiency, and treatment quality for rural patients.

We need more work in non-English languages and cultures.

NLP classifiers can effectively measure "good communication" and this could be very valuable.

Advances in AI science related to synthetic training data and RLAIIF are important.



Thank you!...Questions?

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