This is the podcast for the journal Neuropsychopharmacology. I’m Cynthia Graber.

In-person treatment for substance use disorders is an incredibly important tool, but there’s a high failure rate — more than 50 percent of people who enter drop out within the first month. There hasn’t been a highly accurate method of identifying who might leave and who might succeed, and knowing this could help centers allocate resources to give the right type of assistance to the right people at the right time. One tool available is called the Addiction Severity Index, which is used to help identify the severity of the addiction and thus customize treatment, but it wasn’t developed to gauge whether a patient might drop out entirely. So a team of researchers decided to mine something known as a digital phenotype.

BC: When you are online, when you are using any type of digital tool, you leave a digital trace behind. So when you're on social media, it's an archive of your life. You are posting it in real time, but it stays there until you take it down or the platform closes.

Brenda Curtis is a clinical researcher at the National Institute on Drug Abuse Intramural Research Program, and she’s one of the paper’s authors.

BC: We think about psychology and psychiatry and we think about therapy and people talk, right? I mean, it's talking, it's talking to another person. And there is so much that you can garner from communication, from the words that people say, how they pause, how they hesitate, how fast they go, how quick they are to respond, and the word choice that they use. So why wouldn't we think that we can get that information from the word choices and the things that they're doing online?

So it's not that big of a jump for what we do in traditional therapy. The difference is when you are working in a traditional healthcare center, you are getting things delayed. You're getting things a lot of times after the fact. You're asking people to recall what happened and when it happened and asking them to recall how they felt.

And when you're getting something in real time, you remove that discrepancy. And one of the things that we were really concerned with is that at the beginning of treatment, at intake, that's a very chaotic time. And a lot of times you're gathering a lot of this foundational information at a very chaotic time in a person's life—meaning that maybe there's a better time or better data that you can use instead of relying on self-report.

So how did you set up this study? You relied on Facebook language, right?

BC: Let me give you a little bit of what happened. So a person, they enter treatment, and within their first week we collected their social media language. And that social media language is the language before entering treatment, so two years before entering treatment. And we also did the ASI, which is like an hour-long interview.

Now we have this language that we collected from their social media account, and you've got to process it. So we use BERT, which was or is the foundation for Google search, it's the foundation for Siri, it's the foundation for Amazon Alexa. It's a natural language processing tool that goes through the language and codes it.

We've already, through the years, we have language that we associate using tools like LUKE, which does positive and negative types of language. Whereas BERT is using what you'd call an open vocabulary, where it's looking to see how words associate with other words, split into the group that dropped out of treatment and the group that stayed in treatment.

So okay, you started with about 500 mostly African American men, about half had enough Facebook data that you could use that data for the study. You repeatedly trained the tool on 90 percent of the participants and then used that to predict the other participants, the hold-out group, and then you repeated that. Before we get to the results, I have to ask, isn’t language even within English really particular, depending on your age, your race, your income level? Wouldn’t that affect the results?

BC: So taking a little bit of a step back, unlike a scale, for example, where, when you make it, that's it, with the language models, you have to constantly feed it and correct it. So what you built on one population at one period of time is not going to hold true going forward per se. So you would constantly collect new information and feed it into the model and run your analyses to continue as you go to new populations, as time changes.

But we do have — for example, in the field, not only are you collecting this language, but typically if you're doing this research, you're collecting a lot of other language. And so you're building models already on slang features, positive and negative. You know, when fat goes from F A T to P H A T, right? You catch that. So you're already doing that and that's being fed into your model.

But remember also it's going by an association to a point, so you can pick up when it's a positive and when it's a negative. But yes, these models are not meant to be, you build and walk away from. You build and you keep building.

Great, so now, you followed out the participants for 90 days and used self-report data for whether they relapsed and whether they dropped out of treatment. You ended up using the tool to predict dropping out of treatment, because that was the most important outcome to understand. So how did the system do in terms of predicting remaining in treatment or dropping out?

BC: Figure two gives you the overall predictive accuracy in 90 days looking at the ASI versus the social media language, the digital phenotype, and then combining it. The area under the curve for the ASI was about .65, .66. Whereas for the social media language, the digital phenotype, it was .725. And those were significantly different. So the social media language did much better. But then the best model was when we combined the two, which tells you that they were giving different things. So again, a lot of times I say it's hubris to think that digital phenotyping is going to replace clinical measures. No, I think it's here to compliment clinical measures.

Practically, in the future, how might a clinician use the two together?

BC: What we did was we specifically tested that. I would never ask anyone to drop a clinical measure that's been well validated and well used. So we were like, okay, let's imagine that we were a treatment center, how might we use this?

We said to ourselves, imagine you were a treatment center, and you were able to run this study, and you had the social media language and you had the ASI and you had the demographic. You run the model. And then we gave people a score, the model came out with a score, and we were able to put people from highest to lowest risk.

So if you were a clinician in a treatment center, and someone scored in the highest percentile, the highest quartile, maybe you don't wait two weeks, for example, to get them into a provider. Or maybe you think that, hey, you know, maybe this person really would do well on a medication-assisted treatment. Or we have a counselor, we’ve got two spots open for the person, let's put them in the first one. So that maybe you can triage treatment accordingly.

What are some of the limitations of this study?

BC: Oh, there's host of limitations of this study. First of all, this is a one time, one set piece of time. We need to validate this. While it was different treatment centers, it was people in Philadelphia, at one group of time. So yes, we need to validate it, we need to, as I said earlier, you kind of have to keep building these models. So we need more data.

I would say that there's some newer language models that we would want to also employ that we make it have even better accuracy. So again, it's like your traditional research. We would need to do more of it in order to get there.

And what would you say is kind of your biggest takeaway from this study and the results?

BC: My biggest takeaway is I became very hopeful with this research and these results. This right here is passive data in the sense that it's already out there and it's very fine grain and it's telling us about a person's life in real time that we typically as researchers and treatment providers don't have access to. So it's bringing some new information to the table that we just don't have.

This is the podcast for the journal Neuropsychopharmacology. To read the article discussed in the podcast, go to [www.nature.com/npp](http://www.nature.com/npp). I’m Cynthia Graber.