

## **Clinical Psychology Portfolio**

Kendra Wyant<sup>aff-1</sup>

<sup>aff-1</sup>Department of Psychology, University of Wisconsin-Madison

### **Author note**

Correspondence concerning this article should be addressed to .



## **Background**

### **Personal Statement**

I remember the first computer program I wrote. It started with a menu of mathematical operations that a user could select from. Then, the user was prompted to enter two numbers, and the program returned the result of the calculation. Essentially, I created a complicated calculator! But I was so excited about it. I immediately started thinking of other possibilities - ways I could automate tasks or do more complex operations. Ways I could use code to problem-solve. At the time, coding was a hobby that eventually led to an undergraduate minor. Today, it is an essential part of my research, as I regularly use machine learning and high-throughput computing to answer my research questions.

As I have progressed through my graduate career my clinical interests have increasingly focused on assessment. Similar to how I might piece together code to solve a problem, I enjoy fitting the puzzle pieces from clinical interviews, life circumstances, and cognitive and personality measures to describe a person's needs and recommend solutions that create a holistic picture. I found these experiences to be especially rewarding after receiving positive feedback on a juvenile court evaluation from the youth attorney assigned to the case.

I plan to pursue a career grounded in data science and clinical assessment. I can envision these paths as separate avenues - e.g., working as a clinical scientist with the NIDA Clinical Trials Network and conducting court-ordered assessments on the side. Or, as overlapping - e.g.,

working as research clinician at the VA and providing assessments at the hospital or for the Veterans Treatment Court Program.

To move towards these goals, I plan to gain more relevant research and data science experiences through collaboration and leadership roles. I also intend to audit a course on Bayesian Statistics this Fall and TA for John Curtin's General Linear Model course next year. Clinically, I plan to continue my forensic assessment work with Dr. Patti Coffey. Additionally, I will be gaining experience at the VA this fall, where I can learn what it is like to work in a hospital setting and assess whether this environment aligns with my interests.

### **Supporting documents**

- Current CV
- Unofficial transcript

## **Research Experiences**

### **Research Statement**

In 2022, drug overdoses were the eighth leading cause of death in the United States. The process of recovery, lapse and relapse in substance use disorders is chronic and non-linear. However, unlike other chronic health conditions (e.g., diabetes), substance use disorder treatment is time-limited and aimed at reducing substance use behaviors when individuals are in acute relapse. My research aims to improve substance use disorder treatment by focusing on the continuity of adaptive care that extends beyond initial symptom reduction. Specifically, I am interested in the application of machine learning to personally sensed data for the purpose of algorithm-guided

clinical recommendations (e.g., what intervention or activity would be most helpful for this individual at this moment?) and risk monitoring (e.g., what is the probability that an individual will engage in goal-inconsistent substance use in the next week?).

Personal sensing allows for frequent, longitudinal measurement of changes in proximal risk (e.g., for goal-inconsistent substance use). However, to use these data for algorithm-guided action, we must determine that people with substance use disorders are willing and able to provide these data. Thus, I assessed the feasibility of personal sensing methods by evaluating behavioral and subjective indicators of acceptability among people with alcohol use disorder. We found participants subjectively rated personal sensing methods as being acceptable (on average, ratings were significantly higher than neutral) and that participants were willing and able to adhere to our protocols (Wyant et al., 2023). A current study is underway to attempt to replicate these findings in a national sample of people with opioid use disorder.

A second parallel aim of my research has been to use personal sensing data to predict future goal-inconsistent use of alcohol with high temporal precision. In one study, we demonstrated that we could use ecological momentary assessment data to predict hour-by-hour probabilities of goal-inconsistent use in the next hour, next day, and next week with excellent performance (auROC's  $\geq .90$ ; Wyant & Sant'Ana et al., in press). In a follow-up study, we demonstrated that we can also predict goal-inconsistent alcohol use up to two weeks in the future (e.g., goal-inconsistent alcohol use in the next week starting two weeks from now; Wyant et al., in prep).

Finally, machine learning methods allow us to use high-dimensional data that can better capture complex clinical phenomena, like substance use. In our previous work, we found that feature categories with low contributions to overall model performance still consequentially impacted predictions for some individuals at specific moments. Considering a broad set of features allows us to capture risk-relevant signal for more people and, in turn, use features that are important to a specific individual to select and recommend personalized interventions or treatments.

### **First-Author Publications**

1. **Wyant, K.**, Sant'Ana, S.J., Fronk, G.E., & Curtin, J.J. (in press). Machine learning models for temporally precise lapse prediction in alcohol use disorder. *Journal of Psychopathology and Clinical Science*. preprint

Abstract: We developed three separate models that provide hour-by-hour probabilities of a future lapse back to alcohol use with increasing temporal precision (i.e., lapses in the next week, next day, and next hour). Model features were based on raw scores and longitudinal change in theoretically implicated risk factors collected through ecological momentary assessment (EMA). Participants ( $N=151$ ; 51% male; mean age = 41; 87% White, 97% Non-Hispanic) in early recovery (1–8 weeks of abstinence) from alcohol use disorder provided 4x daily EMA for up to three months. We used grouped, nested cross-validation, with 1 repeat of 10-fold cross-validation for the inner loop and 3 repeats of 10-fold cross-validation for the outer loop to train models, select best models, and evaluate those best models on auROC.

Models yielded median areas under the receiver operating curves (auROCs) of .90, .91, and .94 in the 30 held-out test sets for week, day, and hour level models, respectively. Some feature categories consistently emerged as being globally important to lapse prediction across our week, day, and hour level models (i.e., past use, future efficacy). However, most of the more punctuate, time varying constructs (e.g., craving, past stressful events, arousal) appear to have greater impact within the next hour prediction model. This research represents an important step toward the development of a smart (machine learning guided) sensing system that can both identify periods of peak lapse risk and recommend specific supports to address factors contributing to this risk.

#### Relative contributions:

- conceptualization - 25%
- design - 25%
- analysis - 50%; Collaborated with John Curtin to develop generic functions and supporting code for creating features, running main and baseline models on CHTC, and running parameterized scripts to get model performance metrics.
- writing - 30%; Contributed to original draft, edits, and revisions per reviewer suggestions.

2. **Wyant, K.**, Moshontz, H., Ward, S.B., Fronk, G.E., & Curtin, J.J. (2023). Acceptability of personal sensing among people with alcohol use disorder: Observational study. *JMIR mHealth and uHealth*. <http://dx.doi.org/10.2196/41833>

Abstract: Personal sensing may improve digital therapeutics for mental health care by facilitating early screening, symptom monitoring, risk prediction, and personalized/adaptive

interventions. However, further development and use of personal sensing requires better understanding of its acceptability to people targeted for these mental health applications. We assessed the acceptability of active and passive personal sensing methods in a sample of people with moderate to severe alcohol use disorder (AUD) using both behavioral and self-report measures. This sample was recruited as part of a larger grant-funded project to develop a temporally precise machine learning algorithm to predict lapses. Participants ( $N=154$ ; 50% female; mean age = 41; 87% White, 97% Non-Hispanic) in early recovery (1–8 weeks of abstinence) were recruited to participate in a 3-month longitudinal study. Participants were modestly compensated to engage with active (4x daily ecological momentary assessment; EMA, audio check-in, and sleep quality) and passive (geolocation, cellular communication logs, and text message content) sensing methods that were selected to tap into constructs from Marlatt's Relapse Prevention model. We assessed 3 behavioral indicators of acceptability: participants' choices about their participation in the study at various stages in the procedure, their choice to opt-in to provide data for each sensing method, and their adherence to a subset of the active methods (EMA, audio check-in). We also assessed 3 self-report measures of acceptability (interference, dislike, and willingness to use for 1 year) for each method.  $N=191$  of 192 eligible participants consented to personal sensing. Most of these individuals (88%) also returned 1 week later to formally enroll and begin to provide these data. All participants (100%) opted-in to provide data for EMA, sleep quality, most passive methods (geolocation, cellular communication logs), with 1 participant not providing text message content. Three participants (2%) did not provide any audio check-ins. The average completion rate for all



EMAs was 80% and 94% for 1x daily. The completion rate for the daily audio check-in was 54%. Aggregate participant ratings indicated all personal sensing methods to be significantly more acceptable (all  $p < .05$ ) compared to neutral across subjective measures of interference, dislike, and willingness to use for 1 year. Participants did not significantly differ in their dislike of active compared to passive methods ( $p = .23$ ). However, participants reported a higher willingness to use passive (vs. active) methods for 1 year ( $p = .04$ ). These results suggest that active and passive sensing methods are acceptable to people with AUD over a longer period than has previously been assessed. This was true even for data streams that contained potentially more sensitive information (e.g., geolocation, cellular communications). Important individual differences were observed both across people and methods, which indicate opportunities for future improvements.

#### Relative contributions:

- conceptualization - 50%
- design - 50%
- analysis - 80%; Performed all analyses under supervision of John Curtin.
- writing - 60%; Primary contributor to original draft, edits, and revisions per reviewer suggestions.

#### Co-Author Publications

1. Moshontz, H., Colmenares, A.J., Fronk, G.E., Sant'Ana, S.J., **Wyant, K.**, Wanta, S.E., ... & Curtin, J.J. (2021). Prospective prediction of lapses in opioid use disorder: Protocol for a

personal sensing study. *Journal of Medical Internet Research: Research Protocols*. <http://doi.org/10.2196/29563>

Relative contributions:

- conceptualization - 10%
- design - 10%
- analysis - NA
- writing - 10%

## **Presentations**

1. **Wyant, K.**, Sant'Ana, S.J., Fronk, G.E., & Curtin, J.J. (2024, June). *Using ecological momentary assessment for temporally precise lapse prediction in alcohol use disorder*. Flash talk presented at the 2024 Society for Ambulatory Assessment Conference, Ann Arbor, MI.

Abstract: Ecological momentary assessment (EMA) can support frequent, in-situ, longitudinal measurement necessary for monitoring relapse risk. This study evaluates whether EMA can be used to build machine learning models that predict hour-by-hour probabilities of future alcohol lapses with increasing temporal precision (in the next week, next day, and next hour). Model features were engineered from raw scores and longitudinal change in responses to 4X daily EMAs from participants ( $N=151$ ; 51% male; mean age = 41; 87% White, 97% Non-Hispanic) in early recovery from alcohol use disorder for up to three months. We used grouped, nested cross-validation to select and evaluate the performance of our best models. Models yielded median areas under the receiver operating curves of .89, .90, and .93 in held-

out test sets for week, day, and hour level models, respectively. This confirms EMA can be used to predict alcohol lapses with high sensitivity and specificity for new individuals.

Slides available [here](#)

2. **Wyant, K.** (2024, April). *Precision mental health for substance use disorders using personal sensing*. Capstone Presentation at the 2024 UW-Madison Clinical Psychology Research Symposium, Madison, WI.

Abstract: Substance use disorders are highly prevalent and largely untreated. Digital therapeutics, smartphone apps designed for the purpose of managing, preventing, or treating a disorder, may be well-positioned for scalable continuous care for substance use disorders. They are accessible 24/7 and provide a suite of tools and supports that can be used in conjunction with traditional care or on their own. However, for the full benefits of these apps, people must be able to recognize when they are at high risk, initiate engagement with the digital therapeutic, and choose the appropriate supports and tools in the app. This type of self-monitoring and proactive action can be really hard. Digital therapeutics made smarter by personal sensing can help mitigate these barriers. A smart digital therapeutic incorporates personal sensing data for monitoring individuals longitudinally in their day to day lives and uses these data as inputs into a machine learning algorithm to predict the probability of a lapse and identify the important features contributing to that risk. This process allows researchers and clinicians to capture fluctuations of risk in real time and deliver personalized interventions. However, before smart digital therapeutics can become a reality, we must be able to answer some fundamental questions related to feasibility: 1. Is personal sensing

acceptable to people with substance use disorders? 2. Can personal sensing data be used to predict lapses with high temporal precision? 3. How can the same models be used to inform clinical intervention? In this capstone presentation I begin to answer these questions and explore new directions for personalized treatment of substance use disorders.

Slides available here

3. **Wyant, K.** & Curtin, J.J. (2023, August). *Using high-throughput computing to predict future lapses back to alcohol use*. Presented at the Open Science Grid School HTC Showcase, Madison, WI.

Abstract: Personal sensing is a method for longitudinal measurement in situ. Raw data streams are collected by smartphones, wearable sensors, or other smart devices. These raw data streams can consist of self-reports or more novel data streams such as geolocation, cellular communications, social media activity, or physiology. Subsequent processing can extract psychiatric or health relevant measures of thoughts, feelings, behavior, and even interpersonal interactions. In this presentation I walk through a workflow for processing, feature engineering, and modeling risk of alcohol lapses from personally sensed data using the Center for High-throughput Computing.

Slides available here

4. **Wyant, K.**, Moshontz, H., Ward, S.B., Fronk, G.E., & Curtin, J.J. (2023, March). *Acceptability of personal sensing among people with alcohol use disorder*. Presented at Collaborative Perspectives on Addiction Annual Meeting, Albuquerque, NM.

Abstract: Personal sensing may improve digital therapeutics for mental health care. However, further development and use of personal sensing first requires better understanding of its acceptability to people targeted for these mental health applications. Participants ( $N=154$ ; 50% female; mean age=41; 87% White, 97% Non-Hispanic) in early recovery from alcohol use disorder were recruited from the Madison, WI area. Participants engaged with active (EMA, audio check-in, and sleep quality) and passive (geolocation, cellular communication logs, and text message content) personal sensing methods for up to three months. We assessed the acceptability of these methods using both behavioral and self-report measures. The average completion rate for all requested EMAs was 81%. The completion rate for the audio check-in was 55%. Aggregate participant ratings indicated all methods to be significantly more acceptable (all  $P$ 's  $< .05$ ) compared to neutral across subjective measures of interference, dislike, and willingness to use for one year. Participants did not significantly differ in their dislike of active compared to passive methods ( $P = .23$ ). However, participants reported a higher willingness to use passive methods for one year compared to active methods ( $P = .04$ ). These results suggest both active and passive personal sensing methods are generally acceptable to people with alcohol use disorder. Important individual differences were observed both across people and methods which indicate opportunities for future improvements.

Poster available here

5. **Wyant, K. & Curtin, J.J.** (2021, December). *Personal sensing of smartphone communications to support recovery from alcohol use disorder*. Presented at the 36th Annual First Year Project Symposium, Madison, WI.

Abstract: Alcohol use disorder is a chronic relapsing disease. People with alcohol use disorder must often monitor their risk of relapsing for years. Lapses occur when a person with a goal of abstinence has a drink. These are often referred to as a slip and in isolation are not indicative of relapse. Lapses are, however, often an early warning sign of relapse. People with alcohol use disorder can have difficulty recognizing when they are at a high probability of lapsing. Current digital therapeutics aimed to treat and monitor alcohol and substance use disorders provide treatment resources for people, but they are not able to be helpful in identifying periods of high risk in real time. Personal sensing can be used to improve digital therapeutics by adding this temporal element - when is someone likely to lapse. Our study uses a novel method by combining a passive personal sensing data stream (cellular communication logs) with a more active data stream (self-reported context about communications). Here we show that cellular communication logs likely contain signal related to lapse risk. Additionally, our findings suggest that passively sensed data streams can potentially be as effective as more active data streams. This work sets the foundation for future research into optimizing digital therapeutics for long term lapse risk monitoring.

Slides available [here](#)

6. **Wyant, K. & Curtin, J.J.** (2021, August). *A personal sensing approach to alcohol lapse prediction*. Presented at the 2021 Psychology Research Experience Program Symposium, Madison, WI.

Abstract: Alcohol use disorder is a chronic relapsing disease. People can relapse days, weeks, months, or even years after achieving abstinence. Identifying when an initial lapse will occur is an important goal in preventing lapses, repeated lapses, and relapse. Because of the dynamic nature of lapse risk, traditional treatment, like monthly therapy or biweekly therapy sessions, may not be best suited for monitoring lapse risk and intervening prior to relapse, or a full return to previous drinking behavior. Personal sensing methods offer a tool for capturing fluctuations in lapse risk in real time. One understudied personal sensing method in the substance use literature is cellular communication logs. The present study contextualizes participants' communications with self-report information about their frequently communicated with contacts and seeks to develop a predictive model to predict when someone is at a high risk of lapsing.

Slides available [here](#)

7. **Wyant, K. & Curtin, J.J.** (2021, April). *Personal sensing in clinical research*. Presented at the UW-Madison clinical psychology departmental weekly lunch and learn (virtual).

Abstract: Personal sensing is a longitudinal method for in situ data collection. Raw personal sensing data streams (e.g., sensor or log data) can be used to create measures that act as indicators of mental health constructs. Thus, paving the way for more accessible and timely treatment and intervention options. However, using personal sensing in clinical settings

requires that people accept their use and will sustain the behaviors they require. This presentation provides an overview of the acceptability of various personal sensing data streams individually and in the same context among participants with alcohol use disorder. Future implications of the acceptability of these measures will be discussed in the context of my First Year Project.

Slides available [here](#)

## **Workshop Led**

### **1. Introduction to Regularization**

Organization: LUCID, UW-Madison

Date: June 30, 2021

Description: Led a one-hour workshop on applying regularization to the linear model in the tidymodels framework for students enrolled in the Psychology Research Experience Program at UW-Madison. The workshop involved selecting readings and videos for students to watch beforehand and the creation of two scripts for us to work through together.

Materials available [here](#)

## **Workshops and Trainings Attended**

### **1. AI and Society Seminar**

Instructors: Tim Rogers, Ph.D., and Caitlin Roa, Ph.D.

Dates: September 8, 2021 - May 6, 2022



Description: Interdisciplinary weekly seminar to discuss and apply machine learning and AI concepts.

## 2. Introduction to Structural Equation Modeling Workshop

Instructors: Daniel Bauer, Ph.D. & Patrick Curran, Ph.D.

Dates: May 10 – 12, 2021

Description: An introductory three-day workshop on the application and interpretation of path analysis, confirmatory factor analysis, and structural equation models with latent variables.

## 3. LUCID Training Seminar

Instructors: Tim Rogers, Ph.D., and Caitlin Roa, Ph.D.

Dates: September 2, 2020 - April 30, 2021

Description: Interdisciplinary weekly seminar to work on and discuss scientific communication skills and applications of machine learning.

# Clinical Experiences

## Clinical Orientation Statement

My training has primarily centered on cognitive-behavioral approaches, including cognitive behavioral therapy, exposure therapy, cognitive behavioral analysis system of psychotherapy, and acceptance and commitment therapy. While each of these therapies have unique components, they are not in opposition to one another. I find myself drawing from each of them as toolboxes to personalize therapy to the specific needs of my client. For instance, with one client I was treating for depression, a behavioral activation strategy (e.g., doing the smallest possible step towards a

goal) still seemed too difficult for him. I then switched to an acceptance and commitment therapy technique of framing all of our actions as *towards* or *away* moves. This approach resonated with my client as it was easier for him to recognize his decision to stay on the couch or scrolling on his phone as moving him away from what he wanted. He was then able to make the choice to substitute these actions with ones that moved him towards his goal.

Most of all, I prioritize a strong therapeutic relationship built on trust, empathy, and a genuine interest in helping the client achieve their goals. I often draw on motivational interviewing and Socratic questioning skills to establish this relationship with my clients. A strong foundation has allowed me to appropriately challenge and question clients when needed. To illustrate, I recently had a client who believed they should be happy all the time. To move past this, I had to be firm and blunt that this was not a realistic expectation. Without our established rapport and trust, it is possible that this might have created a rupture in our relationship.

One way I foster these components of evidenced-based therapies and a strong working alliance with my clients is through collaboration and feedback. For example, I routinely use standard assessment outcome questionnaires. I was treating a client for death anxiety and we collaboratively came up with exposures for her to do between session. She reported lower subjective distress with each exposure. However, it was with a Death Anxiety Beliefs and Behaviors questionnaire that I administered pre-, mid-, and post-treatment where we were able to see a stark indicator of improvement.

I also routinely ask clients how they like an activity or how they think therapy is going during our sessions. I have found that sometimes their feedback has resulted in us noticeably

shifting our treatment plan (e.g., switching from cognition-focused interventions to emotion-regulation strategies). Obtaining regular feedback is also important to me, as I believe personalizing treatments to clients' preferences, needs, and stage of readiness requires frequent re-evaluation since these states fluctuate and change over time.

## **Practicum Experiences**

### **1. University Health Services, UW-Madison**

Dates: Fall 2023 - Present

Supervisor: Geoff Brown, LPC

Description: In my practicum role with University Health Services I provide mandated substance use services to undergraduate college students in violation with the Office of Student Conduct and Community Standards. These services consist of evidence-based educational harm-reduction programs aimed to reduce negative consequences of alcohol and cannabis use. Specific interventions include two individual sessions of Brief Alcohol/Cannabis Screening and Intervention for College Students (BASICS, CASICS) or two group sessions of Choices About Alcohol. These interventions draw heavily from motivational interviewing and relapse prevention theory.

Time2Track hours available here

Category	Hours
Intervention	12.3
Support	33.0
Supervision	1.5

## 2. Psychology Research and Training Clinic (PRTC), UW-Madison

Dates: Fall 2021 - Present

Supervisors: Chris Gioia, Ph.D., Linnea Burk, Ph.D., Patricia Coffey, Ph.D.

Description: In my practicum placement at the PRTC, I work with adult individual therapy clients with a wide range of psychiatric diagnoses, including anxiety, depression, personality disorders, obsessive-compulsive disorder, and attention-deficit/hyperactivity disorder (ADHD). My training has primarily been centered on cognitive-behavioral approaches, including cognitive behavioral therapy, exposure therapy, cognitive behavioral analysis system of psychotherapy, and acceptance and commitment therapy. I also have conducted several adult personality (SCID-5-CV, PAI, MMPI-2, MCMI-IV), cognitive (WAIS-IV, WASI-II), and learning disorder/ADHD assessments (WIAT-4, WMS-IV, Conners CPT-3).

Through a community-partnership between the PRTC and Patti Coffey, I have been able to conduct two court-ordered psychological evaluations for children and juveniles in need of protective services. These assessments involved reviewing court records, interviewing collateral contacts and conducting in person clinical interviews with the minor in need of services and their guardians. The final product of these assessments consisted of a report of all testing and conclusions directed to the court. Through the same partnership, I have also had the opportunity to conduct a thorough case record review of more than 10 years of mental health records for an individual while they were incarcerated, conduct a psychological

evaluation for schizophrenia in a carceral setting, and write up a report addressed to the individual's attorney.

In these experiences I have worked with, and continue to work with therapy and assessment clients consisting of community members and students that are diverse in terms of race/ethnicity, sex, age, and mental health symptom severity.

A sample de-identified ADHD assessment report is available [here](#)

A sample de-identified integrated report is available [here](#)

Certification of my clinical competencies by the clinic director can be found [here](#)

Time2Track hours available [here](#)

Category	Hours
Intervention	168.40
Assessment	50.08
Support	319.25
Supervision	94.60

### **Total Clinical Hours**

Category	Hours
Intervention	180.70
Assessment*	104.93
Support*	383.75
Supervision*	112.02

\*Additional hours accrued from supervised Structured Clinical Interviews for DSM-5 for a research study at the Center for Healthy Minds. Time2Track hours available [here](#)

### **Diversity Experiences**

## **Diversity Statement**

Substance use affects people from all backgrounds, and the high comorbidity with severe mental health conditions puts individuals at risk of experiencing trauma, incarceration and housing insecurity. Moreover, treatment disparities are pervasive in substance use treatment. Marginalized communities encounter systemic biases and barriers to treatment access and are disproportionately criminalized for their substance use. Thus, experiences with diverse populations are paramount to my research and clinical interest in addiction and substance use.

One vulnerable population greatly afflicted with mental health and substance use disorders are justice-involved individuals. Recently, opioid overdoses have been reported as the leading cause of death among people returning to their communities from carceral settings. Through my clinical work with Dr. Patti Coffey, I have had the opportunity to work with justice-involved individuals. In one experience, I reviewed over ten years of prison mental health records for an individual incarcerated since he was 18 years old. After my clinical interview with this individual, I determined he met criteria for schizophrenia. He had attempted to get help in prison several times, but was labeled as “drug-seeking” and “malingering” by mental health providers due to his self-reported history of substance use. Another memorable experience I can recall is an interaction with an individual I was screening for eligibility for a trauma-focused group for previously incarcerated individuals. He told me about his experiences with substance use, housing insecurity, and trauma. During these experiences I realized how by listening non-

judgmentally and providing empathy and validation I was able to make a powerful therapeutic connection in just a single interaction.

I am also looking forward to my upcoming position in the PTSD Clinic at the VA this Fall. My interest in evidence-based trauma treatment stems from the high comorbidity of trauma experience and substance use disorders. Expanding my skillset to include trauma treatment will enhance my ability to research and treat clients struggling with substance use. It will also allow me to learn more about veteran culture and work within an integrated healthcare system.

Additionally, I have gained experience working with undergraduate students with first-time offences for alcohol or cannabis use. At the PRTC, I worked with a client with an alcohol use disorder who did not wish to change his alcohol use. These experiences have taught me to meet an individual where they are in terms of the substance use goals and to consider external factors contributing to their substance use.

Through my research, I hope to make ongoing treatment and support for substance use disorders more accessible. Therefore, I have begun to carefully consider how my prediction models and results are interpreted regarding representation. I have helped develop fairness analyses with my lab, which can be reported as transparent benchmarks for how our models perform by specific demographic characteristics. I have also incorporated participant feedback into my research. I am currently working on a project with a student I am mentoring as part of the Psychology Research Experience Program. We are using qualitative data from participants with opioid use disorder that describes their experiences with our data collection methods. We aim to use their own words to assess the feasibility of sensing-assisted treatment and intervention, with a

special emphasis on the stability of acceptability and feasibility across demographic groups with known treatment disparities.

### **Workshop Attended**

1. Empowering people to break the bias habit: Evidenced-based approaches to reducing bias and creating inclusion

March 26, 2021

Speaker: Will Cox, Ph.D.

Description: 3-hour didactic and discussion focussed workshop on concepts of implicit or unconscious biases and assumptions about diverse groups of people by treating the application of such biases as a “habit” and using evidence-based strategies for reducing the application of these biases.

### **Mentorship**

1. Research Mentor

Psychology Research Experience Program (PREP), UW-Madison

Dates: Summer 2024

Description: Serving as a Research mentor for a first generation college student. As part of the program I am engaged in a weekly summer DELTA training workshop that is geared towards mentoring students from underrepresented backgrounds in academia. A copy of the syllabus can be found [here](#).



## 2. Mentor

Maximizing Access to Research Careers Mentor Program, California State University,  
Fullerton

Dates: Fall 2020 – Spring 2022

Description: Served as graduate school mentor for student in program for underrepresented groups in academia. Involved frequent email communication and monthly Zoom meetings.

## 3. Mentor

PREP Alumni Mentor Program, UW-Madison

Dates: Summer 2021

Description: Served as mentor for student in PREP program. Involved email and in-person communication about graduate school and acclimating to Madison for the summer.

## Teaching Experiences

### 1. Graduate Teaching Assistant

Course: Introduction to Applied Machine Learning (IAML)

Dates: Spring 2024

Description: Co-led a weekly lab section. This involved developing an agenda for each session that incorporated topic suggestions from students. I also led a lecture discussion section on using machine learning for explanatory purposes.

Course evaluations for IAML available [here](#)

### 2. Guest Lecture

Wyant K. (2024, March). *Improving treatments for substance use disorders*. Introduction to

Psychotherapy Course (Guest Lecture), UW-Madison Department of Psychology, Madison, WI.

Slides available here

### 3. Reader/Grader

Courses: The Criminal Mind; Introduction to Psychotherapy

Dates: Fall 2021 - Spring 2024

Description: Provided detailed feedback on scientific writing. Graded papers and open ended exam questions.