

PROPOSAL NARRATIVE

Literature Review

In psychotherapy with mental health clients, clinical assessment with standardized questionnaires is used to understand a client's psychological symptoms at the initial visit (i.e., severity of mental health symptoms such as depression), and also to track changes in symptoms to measure treatment success. A developing body of research has revealed the importance of using routine outcome monitoring (ROM) to assess mental health clients' progress on a regular basis (e.g., weekly), which can be used to make necessary adjustments to treatment. ROM appears to be particularly beneficial in identifying clients who are at risk of treatment failure or dropout. Without the results of such measures, clinicians are inclined to highly overestimate the likelihood of treatment success, while underestimating treatment failure (Hannan et al., 2005). However, when clinicians utilize ROM data from measures assessing psychological symptoms, their ability to identify clients at risk of treatment failure greatly increases (Shimokawa, Lambert, & Smart, 2010).

Because of these findings, the use of ROM in psychotherapy clinics has seen an increase in past years. Given the complexity of ROM when using paper-and-pencil measures, there is a growing trend in the field to use computerized or web-based systems for ROM known as a measurement feedback systems (MFS's). An MFS is a software tool that gathers routine outcome data from clients and then gives the clinician feedback about their progress, often in the form of graphs of clients' symptoms across time. There are a variety of these systems available, each with different formats and functions.

Viewing a client's scores on psychological symptom measures and related graphs within an MFS is not sufficient, however, unless clinicians are able to accurately and efficiently interpret the data and identify clients who are in danger of treatment failure. Because of this, some MFS developers have worked to create systems where the clinician is alerted if their client is off track from what would be labeled normal progress (Bickman, Kelley, & Athay, 2012; Cannon, Warren, Nelson, & Burlingame, 2010; Hannan et al., 2005; Lambert, Harmon, Slade, Whipple, & Hawkins, 2005; Youn, Kraus, & Castonguay, 2012). In a meta-analysis of four different studies, Lambert et al. (2005) found that when clinicians received a notification that their client was off track, the clients' symptoms levels were far less severe at the end of treatment than when clinicians were not given these warnings. These findings demonstrate the utility of ROM using an MFS to measure clients' treatment response and make informed treatment decisions. Still, the procedures and algorithms used as the foundation of these MFS's are an area that deserves further attention to make these systems as informative as possible for clinical use.

In past studies focused on modeling client progress, researchers have generally used a formula called the *reliable change index* (RCI) to measure if clients have made significant change that is either positive (i.e., symptom improvement) or negative (i.e., symptom deterioration). The RCI is calculated using methods prescribed by Jacobson and Truax (1991) and refers to the number of

points a client has to change for the change to be statistically “reliable” (i.e., not due to measurement error). The RCI is calculated using the following formula:

$$RCI = \frac{X_2 - X_1}{\sqrt{2(S_E)^2}}$$

where X_1 is a client’s baseline score, and X_2 is that client’s post-treatment (or post-baseline) score. S_E is calculated based on the standard error of measurement for that particular clinical assessment measure.

While the RCI is useful in that it is relatively simple to implement, it also has several pitfalls. The RCI only uses two data points to communicate how the client is progressing, rather than using all available data from ROM, which is often administered weekly. The RCI also ignores the rate of change in symptom levels throughout treatment and does not incorporate the fact that client trajectories may vary in treatment. For example, one client’s symptoms may decrease rapidly in the beginning of treatment and then slow down as treatment progresses, while the opposite may be true of another client.

Another way to assess change in treatment is by modeling trajectories using multilevel modeling and growth curve modeling. Using this method, we can create individualized change trajectories that are dependent upon variables such as weeks in treatment, gender, and age. From these projected trajectories we can predict a clients’ future symptom levels and thus predict treatment failure. This method is advantageous because it uses more than two data points to predict treatment failure and it has the capability to handle missing data points (Lambert & Ogles, 2009). Cannon et al. (2010) successfully used this method to construct change trajectories for the Youth Outcome Questionnaire. They also built a clinical messaging system based on these change trajectories that had as high as 73% accuracy. Although this prior study is useful, there are a myriad of clinical assessment measures used in practice, and thus trajectories must be derived for each individual measure. Research on the typical change trajectories is sparse for many of the most commonly used measures in psychotherapy, and this is an important area for further inquiry.

The Current Study

The goal of this project is to utilize multilevel modeling and growth curve modeling to estimate trajectories of clinical symptoms. My proposed project is based on the developing work of my faculty mentor (Rick Cruz, PhD; Psychology), who is leading the implementation of a new MFS, OwlOutcomes, in the Utah State Community Psychology Clinic. OwlOutcomes enables clinicians to assign clients measures from a large library of measures, and to have immediate access to scores and graphs that they can discuss with their clients. However, norms for longitudinal change in treatment are not yet available in this system. With guidance from my faculty mentor, I will learn the basics of multilevel and growth curve modeling as longitudinal data analysis approaches, and apply these models to clinical data from the USU Community Psychology Clinic. I will focus data analysis efforts on three measures: the Patient Health Questionnaire for depression (PHQ-9), the OASIS, and the Pediatric Symptom Checklist (PSC-

17). With this information, we will eventually be able to integrate these trajectories into the MFS so that clinicians can see how their client is progressing relative to the typical trajectory on these measures.

Given the lack of research concerning change trajectories and the complicated nature of the statistical methodology, multi-site collaboration is essential for progression in this field of research. Virginia Tech, University of Washington, and UCLA are all institutions where clinical research with MFS's is being conducted. As a part of this project, I will travel to one of these sites to further develop collaboration and share methodology developed in this project. I will also consult with researchers at the institution to apply the methodology that I am working on with data from their clinic research database.

This project is significant on a number of different levels. First, since there is little research using growth curve and multilevel modeling to develop norms for longitudinal change in treatment, this project will further establish methods in this area for future researchers to expand upon. Second, this project is a foundational step towards eventually integrating a clinician messaging/warning system into OwlOutcomes for use at the USU Community Psychology Clinic. Information about trajectory norms would ultimately help to improve clinician decision-making in mental health services.

In addition to the significance of this project to clinical practice and decision-making, this project will also help me progress in my academic endeavors. As a dual major in psychology and statistics, I have gained experience in both of these fields separately, but I have not had the opportunity to integrate them. This project largely relies on statistical techniques and models used widely in psychology. I will be able to become familiar with the interface between statistical modeling and clinical psychology in a real world setting. This will help me as I work towards my long-term goal of getting a Ph.D. in clinical psychology with an emphasis on clinical research and statistical methods.

Methods

Participants. Participants will be clients receiving therapy at the Utah State University who are using OwlOutcomes and who have consented to have their data used. Except for obtaining child assent (individual adult and parent consent will happen online), researchers will not have direct contact with participants at any stage of the research.

Measures. Three routine outcome measures will be primarily of interest: the PHQ-9, the OASIS, and the PSC-17. The PHQ-9 is commonly used for tracking the severity of depression symptoms in adults (Kroenke, Spitzer, & Williams, 2001). The OASIS is used to assess the frequency and intensity of anxiety symptoms (Norman et al., 2011). The PSC-17 a parent-reported measure that helps assess a child's psychosocial functioning (Gardner, Lucas, Kolko, & Campo, 2007).

Procedures. A digital research database with data from the measures in the OwlOutcomes system will be constructed as part of Dr. Cruz's study that is at the final stages of IRB approval. For the current study, SQL code will be developed to export the specific data needed for this

project. We will export data from the USU OwlOutcomes clinical research database on Amazon Web Services into a local database (saved on the USU Box.com server).

Analysis. Multilevel modeling and growth curve modeling will be used to formulate average trajectories for each of the measures in question. The statistical program *R* will be used to visualize and formulate these models.

References

- Bickman, L., Kelley, S. D., & Athay, M. (2012). The Technology of Measurement Feedback Systems. *Couple & Family Psychology, 1*(4), 274–284. <http://doi.org/10.1037/a0031022>
- Cannon, J. a N., Warren, J. S., Nelson, P. L., & Burlingame, G. M. (2010). Change trajectories for the Youth Outcome Questionnaire self-report: identifying youth at risk for treatment failure. *Journal of Clinical Child and Adolescent Psychology : The Official Journal for the Society of Clinical Child and Adolescent Psychology, American Psychological Association, Division 53*, 39(3), 289–301. <http://doi.org/10.1080/15374411003691727>
- Gardner, W., Lucas, A., Kolko, D. J., & Campo, J. V. (2007). Comparison of the PSC-17 and alternative mental health screens in an at-risk primary care sample. *Journal of the American Academy of Child and Adolescent Psychiatry, 46*(May), 611–618.
<http://doi.org/10.1097/chi.0b013e318032384b>
- Hannan, C., Lambert, M. J., Harmon, C., Nielsen, S. L., Smart, D. W., Shimokawa, K., & Sutton, S. W. (2005). A lab test and algorithms for identifying clients at risk for treatment failure. *Journal of Clinical Psychology, 61*(2), 155–163. <http://doi.org/10.1002/jclp.20108>
- Jacobson, N. S., & Truax, P. (1991). Clinical significance: A statistical approach to defining meaningful change in psychotherapy research. *Journal of Consulting and Clinical Psychology, 59*(1), 12–19. <http://doi.org/10.1037/0022-006X.59.1.12>
- Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9. *Journal of General*

- Internal Medicine*, 16(9), 606–613. <http://doi.org/10.1046/j.1525-1497.2001.016009606.x>
- Lambert, M. J., Harmon, C., Slade, K., Whipple, J. L., & Hawkins, E. J. (2005). Providing feedback to psychotherapists on their patients' progress: Clinical results and practice suggestions. *Journal of Clinical Psychology*, 61(2), 165–174. <http://doi.org/10.1002/jclp.20113>
- Lambert, M. J., & Ogles, B. M. (2009). Using clinical significance in psychotherapy outcome research: the need for a common procedure and validity data. *Psychotherapy Research: Journal of the Society for Psychotherapy Research*, 19(4-5), 493–501.
<http://doi.org/10.1080/10503300902849483>
- Norman, S. B., Campbell-Sills, L., Hitchcock, C. A., Sullivan, S., Rochlin, A., Wilkins, K. C., & Stein, M. B. (2011). Psychometrics of a brief measure of anxiety to detect severity and impairment: the Overall Anxiety Severity and Impairment Scale (OASIS). *Journal of Psychiatric Research*, 45(2), 262–8. <http://doi.org/10.1016/j.jpsychires.2010.06.011>
- Shimokawa, K., Lambert, M. J., & Smart, D. W. (2010). Enhancing treatment outcome of patients at risk of treatment failure: meta-analytic and mega-analytic review of a psychotherapy quality assurance system. *Journal of Consulting and Clinical Psychology*, 78(3), 298–311. <http://doi.org/10.1037/a0019247>
- Youn, S. J., Kraus, D. R., & Castonguay, L. G. (2012). The treatment outcome package: Facilitating practice and clinically relevant research. *Psychotherapy*, 49(2), 115–122.
<http://doi.org/10.1037/a0027932>

EDUCATION PLAN

- Learn basic data management skills and the method of creating and managing a database.
- Learn the process of conducting multilevel modeling and growth curve modeling analyses using the statistical program *R* and the R studio IDE.
- Develop skills in longitudinal data visualization using R, including learning the *lattice* and *ggplot2* packages.
- Learn about processes of multi-site collaboration in research and data analysis consultation by visiting a partner institution to further develop collaboration and share methodology developed in this project.
- Integrate knowledge learned through classes taken for my statistics major into a psychology/clinical context, which will promote my experience and training for graduate school.