Multimodal and Social Modeling of Client-Therapist Interaction

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remembering Demetrius
my faithful shadow in feline form
my dear Mimi

Abstract

Productive interaction between client and therapist is central to successful therapy, but is often hindered by substantial challenges along the way. During each therapy session, the therapist is constantly assessing the client's symptoms through their behavior. These behaviors may be expressed through multiple channels: verbal spoken language and nonverbal "body language". Therefore, the first challenge we focus on is the *multimodal* aspect of behavior. Another fundamental challenge during therapy is the development and maintenance of a collaborative relationship between the client and the therapist. This relationship develops over the course of several weeks, requiring longitudinal study within and across multiple sessions. Thus, the second challenge we focus on is the *social* aspect of behavior. Finally, we acknowledge the challenge of modeling such complex behavior over time in a manner that is useful for prediction tasks, especially in settings with rich but small datasets. We explore *hybrid modeling*: the combination of data-driven methods frequently used in computational modeling, such as neural networks, with theory-driven methods often preferred in psychology and statistics, such as structural equation modeling. While neural networks allow us to learn complex patterns and make predictions, structural equation modeling allows us to create graph models based on prior domain knowledge or hypotheses.

We pursue the challenge of *multimodal* behavior dynamics through two dimensions: verbal behavior and nonverbal behavior. This work addresses the difficulty of evaluating client symptoms across multiple modalities. The *verbal* component of behavior conveys information not only through high-level message intent, but also through more detailed aspects of speech, such as word choice and sentence structure. We present a multifaceted analysis of the client's spoken language as it relates to their psychological health, including a detailed consideration of lexical, structural, and disfluency components of their speech. The *nonverbal* component of behavior includes behaviors such as facial expressions, gestures, or eye gaze patterns. In particular, we study the ever-prevalent nonverbal signal of gaze aversion patterns and how they provide information about the severity of the client's symptoms.

We pursue the challenge of *social* behavior dynamics in two aspects: turn-taking behavior and entrainment behavior. This work investigates the growth and decline of the collaborative relationship between the client and therapist over the course of multiple dyadic interactions. Through *turn-taking* behavior, interaction participants attempt to maintain the flow of conversation. We recount a detailed analysis of turn-taking behaviors and mirroring of head gestures as they signal the quality of the collaboration between client and therapist. Through *entrainment* behavior, participants synchronize their behavior patterns, whether consciously or subconsciously. We present a modeling of stylistic and content entrainment over multiple sessions as it relates to the client-therapist relationship.

Finally, we pursue the challenge of modeling these complex behavior patterns using *hybrid modeling*, combining data-driven and theory-driven methods for computational behavior modeling. Our objective is to improve the performance of data-driven predictive models, particularly in situations with limited data, by incorporating domain knowledge through theory-driven methods. This thesis specifically focuses on integrating structural equation modeling into traditional computational models. We present a unique approach to *representation learning*: the process of identifying meaningful patterns in data. Our approach utilizes structural equation models to create valuable and meaningful representations for use in larger machine learning models. We further refine this method to support *end-to-end learning*, including simultaneous training of both data-driven neural networks and theory-driven structural equation models. We demonstrate that integrating structural equation modeling into a neural network during the training process can often improve the predictive performance of the model.

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Chapter 1

Introduction

Through psychotherapy, psychologists aim to help people from all walks of life achieve happier, healthier, and more productive lives. Although there are several research-based approaches to psychotherapy, the goal remains the same: to help people work through their problems and develop more effective habits. Psychotherapy has been shown to be highly effective in treating common behavioral health issues, such as depression and anxiety [19, 109]. Individuals with heart problems or other chronic illnesses have been shown to live longer when their physical treatment is augmented with psychotherapeutic treatment [5, 82, 192]. In the United States, approximately one in ten people seek mental health treatment in a given year, with the majority treatment plan including psychotherapy [190].

Psychotherapy is fundamentally based on two key principles. The first one is the *client-therapist relationship*, as this approach to treatment is inherently collaborative. The role of a psychologist is to provide a healthy and supportive environment that allows a client to speak openly with someone who is impartial, neutral, and nonjudgmental. This relationship is by necessity asymmetric: the client opens up to discuss their thoughts and concerns, and the therapist generally does not. This contrasts with the most common friendship and acquaintance social interactions, inherently two-sided relationships in which one side opens up gradually in parallel to the other. Building trust and mutual respect in a therapeutic relationship has the potential to be

a considerable challenge, but the many benefits of doing so are well-established; e.g., reduction in client dropout [70, 117] and improvement in treatment outcomes [32, 112].

The second principle recognizes that most psychological symptoms and concerns have a significant effect on a client's behavior. Abnormal behavior patterns and events have long been linked to the identification of psychiatric symptoms and concerns [25, 182, 206] and are often included as a critical component of the diagnostic criteria themselves [6]. These indicator behaviors span a wide range of modalities on the verbal, vocal, and visual spectra. Averted gaze [181, 206], increased fidgeting [56], heightened [111, 140] or reduced [31, 155] emotional expressivity, and disfluent language [20] are some of the many examples of behavioral markers identified by clinicians as significant indicators of psychological concerns. Although most work in psychology and psychiatry has historically relied on manual annotation of behavior, computational modeling of these and similar behaviors has been met with reasonable success in other domains, such as social rapport [39, 73] or educational tutoring [49, 211]. However, the intersection between symptomatic behavior and social behavior is a challenge unique to the medical domain.

The intersection of these two facets, symptomatic behavior and the client-therapist relationship, presents a unique opportunity for us as human-centered computer scientists. As computation becomes increasingly pervasive in our everyday lives, it also facilitates the discovery and development of new opportunities for communication and interaction. The challenge of supporting complex tasks and mediating difficult interactions has been the focus of considerable study in the fields of human-computer interaction and computer-supported collaborative work, which aim to understand how technology can aid and enhance human interactions.

The central theme of this thesis is the critical examination of computational behavior analysis as an enhancement to the therapeutic process, with a focus on symptomatic behaviors, the development of the client-therapist relationship, and building prediction methods using rich but small datasets. Human behavior is multifaceted, and we approach its study recognizing this complexity. We consider *multimodal* behavior dynamics, acknowledging that alongside spoken language, non-verbal cues such as gesture, facial expression, pose, and gaze also contribute to "body language". We also account for *social* behavior dynamics, understanding that human behavior does not exist in isolation but rather in response and reaction to the behaviors of others. These two dimensions of behavior characterize the essential underlying structure of this work: client symptom severity is principally studied in the context of multimodal behavior, while the client-therapist relationship is principally studied in the context of social behavior. Finally, we aim to synthesize these dimensions through the development of novel *hybrid modeling* techniques. These models blend data-driven methodologies that can analyze and extract patterns, such as neural networks, with theory-driven methodologies that can encode domain knowledge, such as structural equation modeling. These hybrid modeling techniques allow for more effective handling of scenarios characterized by limited data sets but robust prior literature.

In the following Section 1.1, we review the key challenges to the analysis of each of these dimensions of behavior, and the core research topics we aim to address. In Section 1.2, we enumerate by chapter the primary contributions of this work to address these challenges.

1.1 Challenges

The primary aim of this thesis is to explore and assess the role of computational behavior analysis in the future of psychotherapy. Given the complex nature of human behavior, this thesis focuses on three key aspects: the dynamics of multimodal behavior, the dynamics of social behavior, and the novel fusion of data-driven and theory-driven approaches for more effective computational modeling of this complexity.

Multimodal Behavior

Human behavior is inherently *multimodal* in nature. Although we often associate 'communication' with 'conversation', communication consists of far more than simply words — a fact well-established through several decades of study by psychologists who dedicate entire careers to the research of nonverbal behavior [115, 168]. Early research on the various components of communication implied that nonverbal behavioral patterns are considered with significantly more weight than explicitly spoken messages, especially when recognizing emotion or interpreting incongruent modalities [139]. According to modern research, the true proportional significance varies widely depending on the social context and condition [202, 203].

The *verbal* component of communication conveys information through both explicit (linguistic) and implicit (paralinguistic) channels: we consider not only what words are spoken, but also how they are spoken. Beyond the high-level information relayed through spoken messages, much research has established that a moderate amount of information about the speaker's affective state can be inferred directly from surface-level lexical features [8, 81, 187]. On the other

hand, paralinguistic features include aspects of spoken language that surround the explicit message and influence its meaning without altering its content: prosodic elements such as pitch or tempo, non-linguistic vocalizations such as disfluencies (e.g., "umm...", "oh!") or laughter, and turn-taking patterns such as extended silence or repeated interruptions. The unspoken component of communication is commonly referred to as the *nonverbal* component: this component includes behaviors such as facial expressions, gestures, or eye gaze patterns.

A unique challenge of psychotherapy is the reality that many, if not most, psychological symptoms and concerns have a marked impact on a person's behavior, often by definition [6]. In the context of mental healthcare, we must acknowledge that all behavior change is possibly — if not expectedly — influenced by both affective state and psychological health. A significant body of work has focused particularly on the behavior of depressed individuals, finding abnormal patterns in facial expression, voice features, and body movement [36, 45]. However, although depression is the most prevalent mental health diagnosis, psychological concerns can span a much broader spectrum, ranging from psychosis to anxiety to obsessive-compulsion. Each of these diagnoses consists of a range of psychiatric symptoms, most of which have a notable impact on an individual's behavior [6], introducing considerable complexity to the analysis of these interactions.

In summary, it appears undeniable that we must consider human behavior through a variety of modalities — that is, we must consider the *multimodal* dynamics of human behavior. Another important aspect particularly applicable to the domain of mental healthcare is the impact of various psychological symptoms and concerns on an individual's behavior. We know that a great deal of study has been dedicated to the modeling of multiple modalities in the technological fields, and that the influence of psychological health on behavior is a major area of interest within the fields of psychology and psychiatry. However, the synthesis of these two elements is a topic of study in its relative infancy. This intersection is one of the major challenges we aim to address in this work.

To study client-therapist behavior across multiple modalities, we explore the *verbal* (R1.1) and *nonverbal* (R1.2) components of behavior.

Social Behavior

No person exists in a solitary vacuum: we all exist within relationships that we are constantly regulating through *social* behaviors. In every single interaction we have, participants not only convey information about the task or topic at hand, but also indirectly develop a connection between themselves and their conversational partners. Humans leverage a wide variety of strategies to establish and maintain social relationships: e.g., developing rapport through small talk, intimacy through personal disclosure, and respect through politeness. These social behaviors are important not only in casual conversation, but they are also particularly key to the development of any collaborative relationship.

The existing work investigating the importance of the client-therapist relationship has firmly established its significance in ensuring positive treatment outcomes [92, 135]. In particular, much of the psychological literature on this relationship focuses on what is commonly known as the *working alliance* [91]. The working alliance aims to capture the collaborative aspect of the client-therapist relationship, divided into three components: agreement on the overall goal of the treatment, agreement on the tasks required to reach that goal, and the feeling of emotional bond between the participants. The quality of this working alliance between client and therapist plays a crucial role in ensuring many positive therapeutic outcomes, including reduction of the client's symptoms and concerns [62, 91, 92], reduced drug abuse and recidivism [132] improved medication compliance [59], and decreased rates of client dropout [59, 118, 178]. A thorough understanding of the developing relationship between client and therapist is critical to the success of any therapeutic treatment.

Most social interactions pose their own domain-specific challenges, but there are many challenges particular to the domain of psychotherapy. The predominant challenge is the fact that

therapeutic conversations innately involve highly sensitive or personal topics [57]. The process of developing a supportive relationship and 'opening up' to the therapist may therefore at times elicit strong negative emotions such as shame, apprehension, or even fright [134]. The evocation of these challenging emotions is not only common, but often an explicit goal of the treatment: several lines of research have established that high emotional arousal during therapeutic sessions is positively correlated with treatment outcomes across therapeutic approaches and psychiatric symptoms [17, 126, 150].

These high-arousal emotions will frequently have a significant impact on the therapist-client relationship, for better or worse [195]. If the client experiences these emotions, but distances themselves from the therapist and refuses to discuss their emotions, the therapist-client relationship suffers as a result [17, 126], and these cases are considerably more likely to result in client dropout [57]. However, instances in which clients actively approach and explore these emotions with the therapist have been shown to significantly strengthen the therapeutic relationship [66, 195]. As a result, these high-arousal moments of emotional experience have the potential to change the overall trajectory of the treatment.

Through these considerations, an important theme emerges: we cannot consider the behavior of the therapist and client as individuals, but as two interacting members of a *social* dyad. The long-term development of a relationship between participants is key to the success of treatment, but certain short-term events within the interaction also have the potential to drastically impact treatment outcomes. This complex component of behavior is the second major challenge we aim to address in this work.

To investigate the dynamics of the client-therapist relationship, we explore two fundamental aspects of social behavior: *turn-taking* behavior that controls the flow of conversation (R2.1) and *entrainment* behavior that synchronizes conversation patterns between speakers (R2.2).

Hybrid Modeling

In the pursuit of modeling these complex behavior dynamics, researchers from a wide range of disciplines have applied many different approaches, which tend to differ depending on the background of the researchers. Those with a computational or machine learning background often lean towards data-driven methods for analysis, making use of large datasets and nonlinear algorithms, such as neural networks, to uncover patterns and relationships in the data without reliance on any preconceived assumptions. On the other hand, researchers with a psychology or statistics background tend to favor theory-driven methods, such as structural equation modeling, to conduct structured investigations grounded in established theories and prior knowledge, to study complex interactions and generate meaningful insights through hypothesis testing.

Each approach has its own unique strengths and weaknesses. Data-driven methods, for example, enable researchers to model and explore nonlinear and potentially unexpected findings. By studying large datasets, they can uncover hidden patterns and relationships that may not be immediately apparent at the small scale of manual investigation. This approach is particularly useful when the underlying behavior dynamics are complex and difficult to capture through traditional theory-driven methods. However, data-driven methods also have limitations. They rely heavily on the quality, quantity, and representation of the data — rather than domain knowledge or theoretical frameworks — to structure their predictions.

On the other hand, theory-driven methods offer a structured and more intuitive approach to analysis. Researchers can design experiments and use statistical models to represent their hypotheses and existing domain knowledge, allowing for a more targeted investigation and modeling. This approach is valuable when there is prior knowledge or theories that guide the research questions. Leveraging a basic understanding of potential patterns within the data can enhance the examination of its finer details. However, theory-driven methods may overlook unexpected patterns or relationships that could be present in the data. They also require careful design and planning, which can be time-consuming and resource-intensive.

With these factors in consideration, the final section of this thesis explores novel *hybrid models* constructed from both data-driven and theory-driven methods. This approach attempts to enhance the performance of data-driven models by integrating the insights and domain expertise of theory-driven models. We aim to use theory-driven statistical models to build rich, effective representations of our data and its underlying systems. We then integrate these representations with our data-driven predictive models.

We explore this concept using primarily two specific models: structural equation modeling (SEM) and neural networks, as both models are commonly seen as general-use tools in their respective fields of analysis. First, we explore the application of theory-driven statistical models, such as SEM, to enhance *representation learning* for data-driven machine learning models (R3.1). Then, we develop an *end-to-end learning* approach where these steps are trained simultaneously (R3.2).

1.2 Contributions

R1.1. Multimodal Challenge: Verbal Behavior Dynamics (Chapter 2)

- We present an analysis of three forms of spoken language markers as indicators of symptom severity:
  - lexical markers, through a study of the function of words;
  - structural markers, through a study of grammatical fluency; and
  - disfluency markers, through a study of dialogue self-repair.
- We identify multiple language markers indicative of the type and severity of symptoms the client is experiencing.
  - A general lack of using relative language (i.e., 'yesterday', 'lately') is highly indicative of more severe symptoms, regardless of the type of symptom.

- Words of power, such as 'superiority' and 'important', are significantly associated with the severity of "positive" distorted symptoms, such as hallucinations or delusions.
- Linguistic difficulty during cognitive processing, reflected through an increased use of disfluencies — such as repeating oneself or restarting an utterance — can be related to the severity of "negative" reduction symptoms, such as blunted affect and emotional withdrawal.

- We also develop a predictive model to estimate the severity of different forms of symptoms based on the client's use of language.

R1.2. Multimodal Challenge: Nonverbal Behavior Dynamics (Chapter 3)

- We present a computational analysis of gaze aversion during clinical interviews.
- We identify multiple gaze markers indicative of the types of symptoms the client is experiencing.
  - Clients tend to avert their gaze more often during introspective questions when experiencing "negative" reduction symptoms, such as blunted affect and emotional withdrawal.
  - Clients also tend to avert their gaze more often (and especially downward) when experiencing negative symptoms.
  - Clients tend to avert their gaze laterally more frequently when experiencing "positive" distorted symptoms, such as hallucinations or delusions.
- We also develop a predictive model capable of distinguishing between symptom-based subtypes of schizophrenia based on the gaze aversion behaviors of the client.

R2.1. Social Challenge: Conversational Turn-Taking (Chapter 4)

- We present an analysis of head gesture and speaking turn patterns as indicators of the strength of the working alliance between the client and therapist.
- We develop a predictive model capable of predicting participant-reported ratings of working alliance based on behavioral markers of head gestures and speaking turn patterns.
- We present an ablation study comparing the contribution of head gestures and speaking turn patterns on the prediction of working alliance ratings.
    - Head gestures tend to be more indicative of the task-oriented components of the working alliance, while turn-taking behaviors tend to be more related to the emotional component.
- We also present an ablation study comparing the contribution of self and partner behaviors on participants' ratings of working alliance.
    - Participant ratings of the working alliance are largely uninformed by the behavior of the other participant.
    - However, beyond simply being uninformed by the partner's behavior, in certain cases, working alliance ratings are misinformed by the partner's behavior.

R2.2. Social Challenge: Linguistic Entrainment (Chapter 5)

- We present an analysis of stylistic and content entrainment as it reflects participants' self-reported ratings of the working alliance between the client and therapist.
- We identify several markers of working alliance ratings based on the entrainment behaviors of the participants.
    - Stylistic entrainment tends to be associated with the emotional components of the working alliance, while content is more related to the task-oriented components.

    - The linguistic entrainment patterns of the client are significantly indicators of their perception of the working alliance.
    - Therapist linguistic entrainment behaviors have a marked impact on the client's perception of bond.
- We also establish evidence of the importance of considering causality in studying and modeling these relationships.

R3.1. Hybrid Modeling: Representation Learning (Chapter 6)

- We develop a novel approach to representation learning by leveraging theory-driven structural equation models combined with our data-driven machine learning models.
- We present a multiview extension of latent change score models, which facilitates the concurrent analysis of both multimodal and interpersonal behavior dynamics.
- We illustrate the use of this approach to learn multimodal and interpersonal representations of behavior dynamics during one-on-one interaction.
- We demonstrate that this approach achieves improved performance over similar conventional approaches, even when limited by a small dataset.
- We also demonstrate that integration of measurement and estimation uncertainty further improves prediction performance on this task.

R3.2. Hybrid Modeling: End-to-End Learning (Chapter 7)

- We introduce a novel methodology for using statistical modeling to learn effective data representations as part of the training process of a machine learning model.
- We explore the impact of the novel components on the performance of the model, and discuss the implications of these results.

- We demonstrate that the predictive performance of this model surpasses the two-step procedure introduced in Chapter 6.

Part I

Multimodal Behavior

"When the eyes say one thing, and the tongue another, a practiced man relies on the language of the first... How many furtive inclinations avowed by the eye, though dissembled by the lips!"

– Ralph Waldo Emerson, 1860 [54]

Chapter 2

Verbal Behavior Dynamics

The evaluation of psychotic disorders is often complex, as their multifaceted nature is often difficult to quantify. While written language has been previously studied, the analysis presented in this chapter takes the novel approach of examining the rarely studied modality of *spoken* language of individuals with psychosis as naturally used in social, face-to-face interactions. Our analyses expose a series of language markers associated with psychotic symptom severity, as well as interesting interactions between them. In particular, we examine three facets of spoken language: (1) lexical markers, through a study of the function of words; (2) structural markers, through a study of grammatical fluency; and (3) disfluency markers, through a study of dialogue self-repair.

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> Alexandria K. Vail, Elizabeth Liebson, Justin T. Baker, Louis-Philippe Morency. Toward Objective, Multifaceted Characterization of Psychotic Disorders: Lexical, Structural, and Disfluency Markers of Spoken Language. *Proceedings of the Twentieth International Conference on Multimodal Interaction (ICMI 2018)*, Boulder, Colorado, 2018.
> https://doi.org/10.1145/3242969.3243020

2.1 Overview

Psychotic disorders are forms of severe mental illness that cause significant functional impairment and can result in profound lifetime disability and loss of productivity [104]. Assessment of psychotic disorders often relies upon clinical interviews and observation of an individual's day-to-day behaviors, but unfortunately, clinicians put in this role are often bounded by constraints such as time availability, clinician fatigue, or the simple human inability to study all channels of behavior at once. These difficulties necessitate the development of tools for the computational phenotyping of mental illness, which can offer objective support and data analysis to clinicians to aid in assessment and treatment.

When assessing the psychiatric condition of an individual, clinicians rely upon subjective analysis of atypicality in the individual's behavior, such as nonverbal cues, social behaviors, and language use. Critically, these behaviors can also be evaluated through multimodal behavior analysis systems. Although a moderate amount of work has focused on nonverbal behaviors through audiovisual information [200, 212], little work has focused on the language use of these individuals with psychotic disorders. Further, to date, almost all work on language use in psychotic disorders has focused on written texts, such as autobiographical narratives and social media interactions [90, 142]. The present work is one of the first studies to examine *spoken* language use in individuals with psychotic disorders from a computational perspective in clinical settings.

Furthermore, most prior work has examined differences between individuals diagnosed with psychotic disorders and those who are not [28, 42, 102, 142], but few studies have examined behaviors within psychotic disorder groups. The primary line of work to date on symptom-specific written language use focuses on anhedonia, a negative symptom of schizophrenia characterized by a reduction in expression of positive affect [22, 28]. This prior work studies only one specific symptom of schizophrenia and does not yet cover the full range of symptoms expressed by psychotic disorders. The present analysis takes the novel approach of examining language use as

it pertains to a broad range of psychotic symptoms and more fully characterizes an individual's manifestation of the disorder.

In this chapter, we analyze three facets of spoken language use in individuals with psychotic disorders: (1) lexical markers, through a study of the function of words; (2) structural markers, through a study of grammatical fluency; and (3) disfluency markers, through a study of dialogue self-repair. For each of these three facets, we perform single-facet analyses, which will inform our multi-faceted fusion approach. Our multi-faceted interaction analysis is conducted in two parts: a moderation analysis and predictive model building. Our moderation analysis examines how the relationship between an individual's symptom severity and two facets at a time. Our multi-facet predictive models consider the set of features emerging as significant in single-facet analyses as predictors of psychotic symptom severity. We perform our analyses and experiments on a dataset consisting of semi-structured clinical interviews between clinicians and adult individuals with schizophrenia or bipolar disorder recently admitted to an inpatient unit at a major psychiatric facility.

2.2 Psychosis and Language

Extended analysis of language use has the potential to influence the understanding of language dysfunction in psychosis, as well as the potential further development of clinical assessment tools. We examine features at three levels of a participant's language use: *lexical markers*, *structural markers*, and *disfluency markers*. The following subsections detail previous work in these areas. This prior work will inform our single-faceted research described in Section 2.4.

Lexicon

As previously mentioned, any previous studies implementing lexical analysis have (1) focused on written language and (2) compared between psychotic disorder and control groups [28, 42, 102].

However, few studies have examined research within psychotic disorder groups to investigate whether word use is linked with psychotic symptoms themselves. For our lexical marker analyses, we focus on five lexical categories, which we introduce as part of three main groups: affect, power, and reality monitoring.

Affect. The foremost line of study of this topic is focused on anhedonia [22, 28], a negative symptom of schizophrenia characterized by a reduction in expression of positive affect. Cohen et al. observed that participants exhibiting high levels of anhedonia used more negative affect words when discussing pleasant topics than those exhibiting low levels of anhedonia [42]. In our analysis, we follow this line of work by investigating *affect* words as they relate to the broader spectrum of psychotic symptoms.

Power. The most characteristic symptoms of psychotic disorders revolve around delusions and grandiosity [107]. Individuals that express high levels of delusion tend to hold beliefs which are unfounded, unrealistic or idiosyncratic [107]. Grandiosity, on the other hand, involves an exaggerated self-opinion and unrealistic convictions of superiority, which can include delusions of extraordinary abilities, wealth, knowledge, fame, power, or moral righteousness [107]. Our analysis examines the impact of delusions and grandiosity on the language of individuals with psychotic disorders via words of *power*: words relating to the drive for influence and dominance.

Reality monitoring. Another significant segment of the lexicon examined in the present analysis involves words related to *reality monitoring* [100]. The concept of reality monitoring extends from the idea that people recall information from two primary sources: external sources (such as perceptual processing and contextual information) and internal sources (such as reasoning). Reality monitoring refers to the processes people use to decide whether information was generated from an external source or an internal source.

Numerous studies have observed reality monitoring impairments in individuals with psychotic disorders compared to healthy controls [58, 61, 108], but most work focuses on the neurocognitive aspects of the phenomenon, rather than detection in the field. The present analysis

takes the novel approach of investigating reality monitoring as it manifests in conversational settings (i.e., spoken language). In particular, it features a focus on the use of words that reflect each of the two potential sources of information: external sources through *perceptual processing* and *relative* (contextual) words, and internal sources through *cognitive processing* words.

Language Structure

Individuals with speaking disorders or cognitive impairment tend to express themselves atypically compared to control groups [60]. Prior work on written language has used language models to study this phenomenon by estimating the probability of a given utterance being produced, e.g., in studies of language impairment in children [60] and language dominance prediction in multilingual individuals [188]. Hong et al. conducted a study of autobiographical narratives written by individuals with and without schizophrenia; this work suggested that different language models optimally explain part-of-speech tag sequences within the two groups [90].

Few previous studies have examined perplexity itself as a measure of grammatical integrity in schizophrenia and psychosis. A study by Mitchell et al. compared posts by social media users voluntarily self-labeled as experiencing schizophrenia against posts from a control group; a marginal difference between these sets of users suggested that those with schizophrenia generated higher-perplexity posts than the control group [142]. The present study takes the novel approach of investigating perplexity as an indirect measure of psychotic symptom severity, rather than as a distinguishing characteristic between individuals with psychotic disorders and those without.

Disfluency

Disfluencies, such as self-repairs, pauses, and fillers (such as *er* and *umm*) are pervasive in day-to-day dialogue [180]. These disfluencies are generally regarded as symptomatic of problems in communication, whether caused by production or self-monitoring issues [130]. Disfluencies can

also highlight the interactive nature of dialogue — some disfluencies occur as a result of tailoring dialogue to a specific listener, or in response to feedback from interlocutors [69].

Individuals with psychotic disorders tend to have difficulties with language and social cognitive skills, and especially with self-monitoring [99] and turn-taking [143], but little research has examined how these problems affect interaction. Work by Leudar et al. found that the less self-repair that an individual with schizophrenia employs, the more verbal hallucinations they tend to experience [129]. Further work by McCabe et al. discovered that other-initiated repairs (clarification of a clinician's dialogue, in particular) are associated with improved adherence to treatment [138]. The present work, therefore, examines the disfluencies and self-repairs present in the dialogue of individuals with psychotic disorders as they relate to symptom severity.

2.3 Dyadic Psychosis Interview Dataset

The dataset examined in the present analysis consists of a series of clinical interviews with adult individuals recently admitted to an inpatient psychotic disorder unit at a major psychiatric facility. Video and audio recordings, as well as transcripts, were collected from 53 sessions (28 unique participants). Each session consisted of a semi-structured clinical interview between the admitted individual and a clinician, lasting approximately 10–15 minutes each. The interview script was modeled upon existing everyday clinical interactions designed to elicit reactions that may be illustrative of the psychiatric condition of the individual[1]. A list of interview questions is presented in Table 2.1.

Following the conclusion of each interview, each participant was administered a series of clinical scales, including the Positive and Negative Syndrome Scale (PANSS) [107], a scale used for measuring psychotic symptom severity. PANSS involves seven-point ratings of 30 symptoms across three dimensions: *positive symptoms*, involving behaviors in excess or distortion of nor-

[1] Although participants varied regarding previous exposure to interactions of this type, this diversity is reflective of the larger population, and we believe that this strengthens the applicability of this analysis.

TABLE 2.1
List of interview questions administered during the session.

What brought you into the hospital?
Has anything in particular been on your mind?
What has the team here been helping you with?
Would you say that they are doing a good job?
What are your goals for the hospitalization?
How are people treating you?
How is the food?
How is your mood? / How are your spirits?
How is your thinking/focus?
How is your energy?
How have you been sleeping?
How is your self-confidence compared to how it usually is?
What changes do you observe since you were hospitalized?

mal function; *negative symptoms*, involving behaviors diminished or suppressed below normal function; and *general psychiatric symptoms*, involving items that cannot be linked decisively to either syndrome. In this chapter, we focus on the symptoms from the positive and negative scales (see descriptions in Table 2.2). The average positive scale score in the present sample is $\mu = 14.88$ ($\sigma^2 = 7.82$), and negative scale score $\mu = 12.14$ ($\sigma^2 = 4.71$), both in a possible range of 7 to 49 (see Figure 2.1 for the distribution of the present sample).

For the following analyses, the dataset was separated into a training set (43 sessions) and a held-out test set (10 sessions). The single-facet analyses were performed upon the training set, and only the multi-faceted predictive models were tested upon the held-out test set after the analysis.

2.4 Single-Facet Language Analysis

Our first set of analyses examines spoken language use at three levels of a participant's dialogue: lexical markers, structural markers, and disfluency markers. The following subsections detail the

TABLE 2.2
Enumeration and brief description of a selection of symptoms contained in the PANSS positive and negative scales [107].

Scale Item	Brief Description of Behavior
Positive Scale	
Delusions	Beliefs which are unfounded, unrealistic, and idiosyncratic.
Conceptual Disorganization	Disorganized process of thinking characterized by disruption of goal-directed sequencing, e.g., circumstantiality, tangentiality, loose associations, non-sequiturs, gross illogicality, or thought block.
Hallucinatory Behavior	Verbal report or behavior indicating perceptions which are not generated by external stimuli. These may occur in the auditory, visual, olfactory, or somatic realms.
Grandiosity	Exaggerated self-opinion and unrealistic convictions of superiority, including delusions of extraordinary abilities, wealth, knowledge, fame, power, and moral righteousness.
Hostility	Verbal and nonverbal expressions of anger and resentment, including sarcasm, passive-aggressive behavior, verbal abuse, and assaultiveness.
Negative Scale	
Blunted Affect	Diminished emotional responsiveness as characterized by a reduction in facial expression, modulation of feelings, and communicative gestures.
Emotional Withdrawal	Lack of interest in, involvement with, and affective commitment to life's events.
Poor Rapport	Lack of interpersonal empathy, openness in conversation, and sense of closeness, interest, or involvement with the interviewer. This is evidenced by interpersonal distancing and reduced verbal and nonverbal communication.
Difficulty in Abstract Thinking	Impairment in the use of the abstract-symbolic mode of thinking, as evidenced by difficulty in classification, forming generalizations, and proceeding beyond concrete or egocentric thinking in problem-solving tasks.
Lack of Spontaneity and Flow of Conversation	Reduction in the normal flow of communication associated with apathy, avolition, defensiveness, or cognitive deficit. This is manifested by diminished fluidity and productivity of the verbal-interactional process.

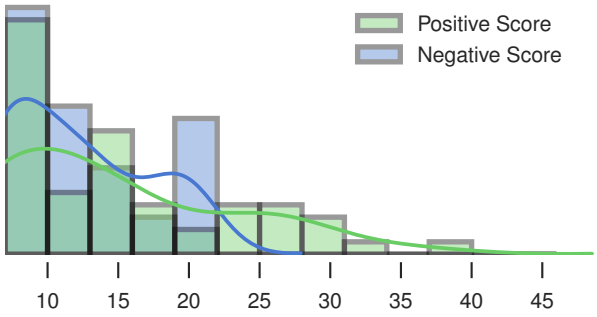

FIGURE 2.1
Distribution of PANSS positive and negative scores in the examined sample.

computational analyses of these three facets of spoken language. The results of these single-facet analyses will be used during the multi-faceted prediction task.

Lexicon Analysis

In this study, we focus on five categories of lexical markers: cognitive processing words, affect words, power words, relative words, and perceptual processing words (see Section 2.2 for details). Lexical features of participant speech were extracted using the Linguistic Inquiry and Word Count (LIWC) tool [154], a computerized measure that assesses speech and language content using a dictionary of over 4500 words across over 60 categories. LIWC has demonstrated validity in measuring expression in verbal dialogue [103] and has been used previously to assess word use in schizophrenia for written text [28, 42]. We computed a Spearman's rank correlation coefficient to assess the relationship between each of these categories and two PANSS scales (positive and negative). To account for multiple hypothesis testing, results were filtered within each scale using the Benjamini-Hochberg procedure, with a family-wise error rate of $\alpha = 0.05$. All analyses were performed upon the training set only. Results are reported in Table 2.3; significant correlations are discussed below and illustrated in Figure 2.2.

Affect. Affect words relate to the emotions: for example, *happiness*, *gloomy*, and *sadly*. Previous work has suggested that greater levels of emotion are significantly associated with lower

TABLE 2.3
Reported Spearman's rank correlation coefficient between selected LIWC features and PANSS scores. Boldface indicates significant correlations holding under a Benjamini-Hochberg procedure for multiple hypothesis testing, where $\alpha = 0.05$.

	Positive Score		Negative Score	
	corr(ρ)	p-value	corr(ρ)	p-value
Cognitive Processing	$+0.048$	0.736	$+0.018$	0.898
Affect	-0.063	0.655	$\mathbf{+0.287}$	$\mathbf{0.037}$
Power	$\mathbf{+0.374}$	$\mathbf{0.006}$	$+0.091$	0.516
Relative	$\mathbf{-0.302}$	$\mathbf{0.028}$	$\mathbf{-0.352}$	$\mathbf{0.010}$
Perceptual Processing	$\mathbf{+0.351}$	$\mathbf{0.010}$	$+0.111$	0.429

functioning in psychotic disorders [22], and expression of negative affect, in particular, has been linked to anhedonia, a major negative symptom, in the past [42]. There was a significant positive correlation between affect words and negative PANSS score ($\rho(53) = +0.287$, $p = 0.037$). The more negative symptoms expressed by a participant, the more affect words they used.

Power. Power words relate to the drive for dominance: for example, *superiority*, *important*, and *exploit*. Individuals with psychotic disorders often exhibit symptoms of grandiosity and delusions, which are associated with a perception of greater self-power [107]. There was a significant positive correlation between power words and positive PANSS score ($\rho(53) = +0.417$, $p = 0.002$). Overall, the more positive symptoms expressed by a participant, the more power words they used.

Reality monitoring. Relative words relate to situations regarding time and space: for example, *yesterday*, *lately*, and *nearby*. These words relate to the phenomenon of reality monitoring, and particularly to the attachment of information to external stimuli [100]. There was a significant negative correlation between relative words and negative PANSS score ($\rho(53) = -0.381$, $p = 0.005$), as well as a significant negative correlation between positive PANSS score ($\rho(53) = -0.302$, $p = 0.028$). We can infer from this result that the more positive or negative symptoms expressed by a participant, the fewer relative words they used.

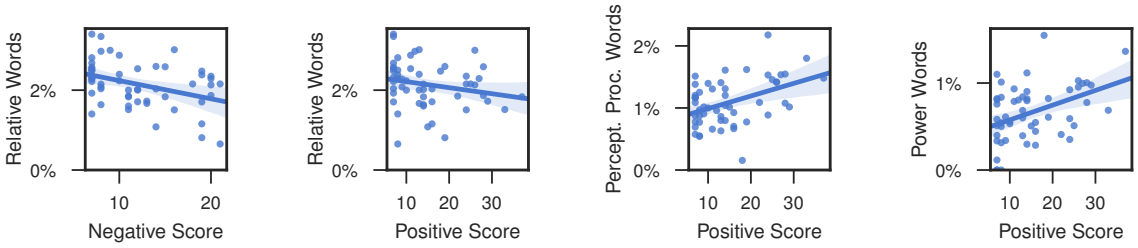

FIGURE 2.2
Regression plots of four of the significant correlations between LIWC features and PANSS scores.

Perceptual processing words relate to the senses: for example, *feeling*, *see*, and *listened*. Like relative words, these words also tend to relate to reality monitoring, and these words are also linked to the perception of external stimuli [100]. There was a significant positive correlation between perceptual processing words and positive PANSS score ($\rho(53) = +0.434$, $p = 0.001$). Overall, the more positive symptoms expressed by a participant, the more perceptual processing words they used.

Language Structure Analysis

The structure of the language — including vocabulary and syntactic constructions — expressed by a participant can be measured via *perplexity*, a measurement based on entropy, and can be interpreted to roughly estimate how predictable is a sequence of words. The present work trains a trigram backoff language model on the Switchboard corpus [67], a sizable multispeaker corpus of conversational speech and text through telephone conversations about varying topics. This corpus can be viewed as an approximation of non-psychotic disorder spoken dialogue. The model is then tested on the transcript of each session, and the overall perplexity is calculated. A Spearman's rank correlation coefficient is computed to assess the relationship between perplexity and each of the PANSS scales. All analyses were performed upon the training set only.

Results. The results suggest no significant correlation between negative PANSS score and perplexity ($\rho(53) = -0.046$, $p = 0.746$), but a significant positive correlation between positive

PANSS score and perplexity ($\rho(53) = +0.313$, $p = 0.022$). The more positive symptoms an individual expresses, the higher the perplexity of their utterances. Individuals high in positive scale symptoms tend to express symptoms such as excitement and conceptual disorganization, which may interfere with sentential construction [107].

Disfluency Analysis

Disfluencies in the form of speech repair are typically assumed to have a tripartite *reparandum-interregnum-repair* structure [184], as illustrated in the following example.

$$\text{“John} \quad [\quad \underbrace{\text{likes}}_{\text{reparandum}} \quad \underbrace{\text{uh}}_{\text{interregnum}} \quad \underbrace{\text{loves}}_{\text{repair}} \quad] \quad \text{Mary”}$$

A *reparandum* is an error in speech that is subsequently corrected by the speaker; a *repair* term is the corrected speech. An *interregnum* term is a filler token or a cue phrase between the reparandum and repair terms, often a stalling measure while the speaker generates the repair term.

We examine three forms of disfluencies: edits, repeats, and restarts. If the reparandum and the repair terms are absent, the disfluency is considered to be reduced to an isolated *edit* term. In this canonical example, the interregnum is a pause filler token (“uh”), but more phrasal terms such as “I mean” and “you know” are also often used.

The other two forms of repair we examine in the present analysis are *repeat* terms and *restart* terms. The occurrence of a *repeat* term is reasonably straightforward — this is when an individual repeats a word or a short phrase. A *restart* term occurs when an individual changes a partially complete spoken utterance, as in the example above.

Self-repairs were annotated automatically using a deep-learning-driven incremental disfluency detection model developed by Hough et al. [94]. This model consists of deep learning sequence models that consume incoming words and use word embeddings, part-of-speech tags,

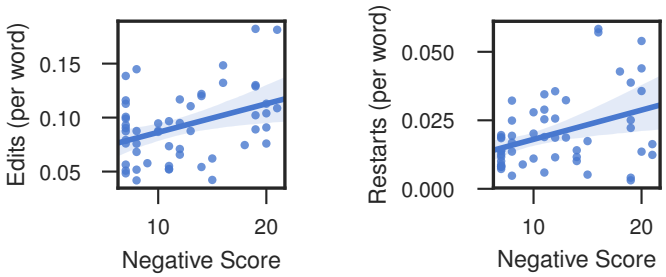

FIGURE 2.3
Regression plots of the significant correlations between self-repair features and PANSS scores.

and other features to predict disfluency labels for each word in a strictly left-to-right, word-by-word fashion.

Similar to the lexicon analysis, a Spearman's rank correlation coefficient was computed to assess the relationship between each type of self-repair and each PANSS scale (positive and negative). To control for multiple hypothesis testing, results were filtered within each scale using the Benjamini-Hochberg procedure, with a family-wise error rate of $\alpha = 0.05$. All analyses were performed upon the training set only.

Results. Results are reported in Table 2.4; significant correlations are discussed below and illustrated in Figure 2.3. Both significant correlation results are related to negative PANSS score. The negative PANSS score is characterized by symptoms such as poor rapport, difficulty in abstract thinking, and lack of spontaneity and awkward flow of conversation [107]. There was a significant positive correlation between the negative PANSS score and edit terms ($\rho(53) = +0.309$, $p = 0.024$) as well as a significant positive correlation between the negative PANSS score and restarts ($\rho(53) = +0.334$, $p = 0.014$). The more negative symptoms expressed by an individual, the more edit terms and restarts they express.

TABLE 2.4
Reported Spearman's rank correlation coefficient between selected self-repair features and PANSS scores. Boldface indicates significant correlations holding under a Benjamini-Hochberg procedure for multiple hypothesis testing, where $\alpha = 0.05$.

	Positive Score		Negative Score	
	corr(ρ)	p-value	corr(ρ)	p-value
Edits	-0.089	0.525	$\mathbf{+0.309}$	**0.024**
Restarts	$+0.173$	0.217	$\mathbf{+0.334}$	**0.014**
Repeats	$+0.028$	0.844	$+0.215$	0.123

Discussion

In this section, we summarize our observations for all three facets of spoken language: lexical markers, structural markers, and disfluency markers. For lexical markers, we group our observations following the three lexical category groups introduced in Section 2.2.

Affect. Our analyses investigated a series of lexicon categories as used by individuals with psychotic disorders (Section 2.4). There existed a positive correlation between affect words and negative symptoms: the more affect words an individual used, the more severe their negative symptoms. Interestingly, this counters the intuition regarding the negative symptom of emotional withdrawal and blunted affect [107]; one might believe that an individual with severe negative symptoms may not be very forthcoming about their emotions. This result relates to prior work on anhedonia, which suggested that individuals with this negative symptom do not use significantly fewer affect words than those without, but instead use affect words with a more negative valence [22].

Power. Another result involves power words: the more power words an individual expresses, the higher the severity of their positive symptoms. Some characteristic positive symptoms include delusions and grandiosity, which involve holding beliefs that are unfounded, unrealistic, or idiosyncratic, exaggerated self-opinion, and unrealistic conventions of superiority [107]. Considering that these symptoms are central to the positive symptom scale, this finding represents a useful contribution toward computational phenotyping of psychotic disorders.

Reality monitoring. Two lexicon categories emerged that are related to reality monitoring: relative words and perceptual processing words, both of which are related to information recall from external sources [100]. Relative word use is negatively associated with both negative and positive symptoms: that is, the more severe the psychotic symptoms an individual expresses, the less they speak in relative terms. It is interesting to see that this correlation holds for both symptom scales; this may be an indication of a general difficulty in psychotic disorders, rather than dependent on its manifestation. This result reinforces the findings from previous studies that suggested that reality monitoring impairments are generally characteristic of psychotic disorders [58, 108]. There was also a positive association between positive symptoms and perceptual processing: the more perceptual processing words an individual used, the more severe their positive symptoms. Unlike relative word use, perceptual processing word use appears to be dependent upon the particular manifestation of the disorder: one of the characteristic positive symptoms is hallucinatory experiences, which may lead to an individual being more aware of their surroundings, real or imagined, which in turn leads to more discussion about what they feel, see, and hear.

Structure. A correlation was discovered between positive symptom severity and language perplexity (Section 2.4). Positive symptoms entail higher-activity behaviors exceeding typical function, so individuals expressing these symptoms acutely may experience difficulty in constructing sentences; this follows from previous work suggesting that individuals with cognitive impairment may express themselves atypically compared to control groups [60].

Disfluency. There were two results regarding self-repairs during dialogue (Section 2.4). In particular, negative symptom severity was positively correlated with both edit terms and restarts. Disfluencies are generally regarded as symptomatic of problems in communication [130]. Individuals with high negative psychotic symptom severity characteristically experience problems in communication through poor rapport and flow of conversation [107]; it follows logically that this may be expressed linguistically through dialogue disfluencies.

2.5 Multi-Faceted Language Analysis

Building from the results of the single-facet computational analyses, we are interested in examining the interactions between the different facets of spoken language. In this section, we leverage these results in two multi-facet analyses: an analysis of moderation and predictive modeling. The moderation analysis will focus on two facets at a time, while the predictive modeling will integrate all three facets.

Moderation Analysis

Each of the two PANSS scales (positive and negative) were examined as a moderator of the relation between each of the lexicon features and each form of self-repair. In other terms, the analysis focused on how individuals expressing high positive or negative symptoms might self-repair more frequently when speaking on particular topics (see Figure 2.4 for an illustration). This work is conducted as a form of regression analysis [43]. Given a PANSS score X_S and a lexicon feature X_L, we predict a given dependent variable (i.e., a self-repair feature) Y_R with the model

$$Y_R = \beta_S X_S + \beta_L X_L + \beta_{SL} X_S X_L, \tag{2.1}$$

such that β_S, β_L, and β_{SL} are learned parameters via ordinary least squares on the training set [161]. For example, Y_R could indicate self-repair repeats, while X_S and X_L indicate positive PANSS score and affect words, respectively. We describe below three moderation models with significant interactions.

Negative symptoms, affect, restarts. The first model involves negative PANSS score, affect words, and restarts (see Figure 2.4a). In the first step of the regression analysis, negative PANSS score and affect words are entered as predictors of restarts; this model significantly predicted restarts ($F(50, 2) = 4.797$, $p = 0.012$, $r = +0.401$). In the second step of the analysis, the

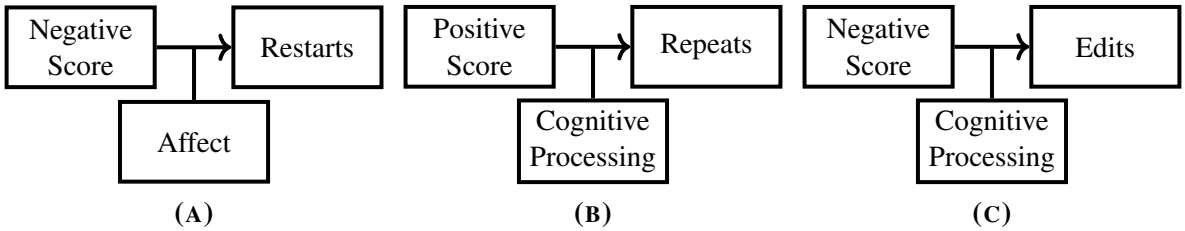

FIGURE 2.4
Illustration of the structure of the moderation analyses with significant interaction effects described in Section 2.5.

interaction term (the product of the negative PANSS score and affect word use) was introduced; this model also significantly predicted restarts ($F(49, 3) = 4.733$, $p = 0.006$, $r = +0.474$). This difference was statistically significant ($\Delta r = +0.073$, $p = 0.050$). See Table 2.5a for the final interaction model; β is the coefficient for each term, and t and p refer to a t-test value and p-value indicating its significance. From these results, we can observe that the higher an individual's negative PANSS score and the more affect words they used, the more they restarted their sentences, but when high-negative-score individuals spoke about affective utterances, they expressed *fewer* restarts than in general.

Positive symptoms, cognitive processing, repeats. The second model involves positive PANSS score, cognitive processing words, and repeats (see Figure 2.4b). In the first step of the regression analysis, positive PANSS score and cognitive processing words are entered as predictors of repeats; this model marginally predicted repeats ($F(50, 2) = 1.952$, $p = 0.153$, $r = +0.269$). In the second step of the analysis, the interaction term (the product of the positive PANSS score and cognitive processing word use) was introduced; this model did significantly predict repeats ($F(49, 3) = 2.754$, $p = 0.052$, $r = +0.380$). This difference was statistically significant ($\Delta r = +0.111$, $p = 0.048$). See Table 2.5b for the final interaction model; β is the coefficient for each term, and t and p refer to a t-test value and p-value indicating its significance. From these results, we can observe that the higher an individual's positive PANSS score, and the more cognitive processing words they used, the more repeats in their dialogue, but when high-positive-score individuals spoke about cognitive processing terms, they expressed *fewer* repeats

TABLE 2.5
Regression models examining the moderation between PANSS scores and lexical categories as predictors of self-repairs.

(A)

Restarts =	β	t	p
Affect Words	$+0.468$	$+1.443$	0.155
Negative PANSS Score	$+1.107$	$+2.947$	0.005
Interaction Term	-1.020	-2.006	0.050

(B)

Repeats =	β	t	p
Cognitive Processing Words	$+0.335$	$+1.116$	0.270
Positive PANSS Score	$+2.255$	$+2.168$	0.035
Interaction Term	-2.171	-2.028	0.048

(C)

Edits =	β	t	p
Cognitive Processing Words	-1.278	-1.568	0.123
Negative PANSS Score	-0.572	-1.716	0.092
Interaction Term	$+1.788$	$+2.070$	0.044

than in general.

Negative symptoms, cognitive processing, edits. The third model involves negative PANSS score, cognitive processing words, and edits (see Figure 2.4c). In the first step of the regression analysis, negative PANSS score and cognitive processing words are entered as predictors of edits; this model significantly predicted edits ($F(50, 2) = 4.559$, $p = 0.015$, $r = +0.393$). In the second step of the analysis, the interaction term (the product of negative PANSS score and cognitive processing word use) was introduced; this model also significantly predicted edits ($F(49, 3) = 4.667$, $p = 0.006$, $r = +0.471$). This difference was statistically significant ($\Delta r = +0.078$, $p = 0.044$). See Table 2.5c for the final interaction model; β is the coefficient for each term, and t and p refer to a t-test value and p-value indicating its significance. From these

results, we can observe that the higher an individual's negative PANSS score, and the more cognitive processing words they used, the fewer edits in their dialogue, but when high-negative-score individuals spoke about cognitive processing terms, they expressed *more* edits than in general.

Discussion. There were three significant results observed during our moderation analysis. In particular, as individuals speak of specific topics, individuals with more severe symptoms tend to repair their language more or less often than in general. For example, individuals with high levels of negative symptoms were much less likely to restart their sentences when speaking about affective topics than in general, which may be explained by the blunted affect symptoms; it may be more straightforward for these individuals to speak about their emotions if they are not experiencing many of them. In another case, individuals with more severe positive symptoms were less likely to repeat themselves when speaking with cognitive processing terms, and individuals with more severe negative symptoms were more likely to edit themselves when speaking with cognitive processing terms. These three results are hinting to the fact that there are multi-faceted interactions in spoken language of individuals with psychotic disorders. Following these intuitions, we next learn multi-faceted prediction models.

Predictive Modeling

The final multi-faceted analysis consisted of the development of two sets of predictive models, one for each of the PANSS scales: positive and negative. Each model includes features that appeared as significant in the single-faceted analyses (see Section 2.4). For the positive PANSS scale, the features are the lexicon categories of power words and perceptual processing words, as well as perplexity. For the negative PANSS scale, the features are lexicon category of time words and the self-repair features of edits and restarts. As previously mentioned, all the single-facet analyses were performed on the training set, allowing for a fair evaluation of the prediction models on the test set (with new participants not in the training set).

Prediction experiments. We compare both ϵ-support vector machines [50] and multi-layer

TABLE 2.6
Mean Pearson's r correlation coefficient achieved over ten-fold cross-validation, hold-out testing on prediction of positive and negative PANSS scores.

PANSS Scale	SVM	MLP
Positive Scale	$+0.570$	$+0.879$
Negative Scale	$+0.566$	$+0.710$

perceptron models [83] for prediction of PANSS scales. These models were trained using ten-fold cross-validation for hyperparameter tuning on the training set, optimizing upon the Pearson's r correlation coefficient. Hyperparameters included the kernel (linear or radial basis function), $C = \{10^{-5}, 10^{-4}, \ldots, 10^{4}\}$, $\epsilon = \{10^{-5}, 10^{-4}, \ldots, 10^{-1}\}$, and $\gamma = \{0.00, 0.05, \ldots, 1.00\}$ (in the case of the RBF kernel) for the support vector machines, and the number of hidden units ($\{1, 5, 10, 50, 100, 500\}$) and activation function (logistic, hyperbolic tangent, or rectified linear unit) in the multi-layer perceptron. Test set results are summarized in Table 2.6. The multilayer perceptron significantly outperformed the SVM in both cases ($p < 0.01$ in both cases according to a one-way ANOVA).

Feature analysis. To examine the relative importance of the included features in the multi-layer perceptron model, a greedy step-wise feature selection process was performed, using a ten-fold cross-validation procedure over the entire set[2]. At each iteration, candidate features were evaluated, and the single best feature to be added was selected via the highest average change in Pearson's r (Δr). Results are summarized in Table 2.7.

Discussion. In our predictive modeling analysis, we compared the performance of support vector machines (SVMs) and multi-layer perceptrons on a prediction task for positive and negative symptom severity. Although SVMs performed reasonably on both tasks, they were outperformed by multi-layer perceptrons in both cases. A higher performance was observed in predicting positive symptom severity, which may suggest that an individual's language use is more reflective of positive symptoms than negative symptoms in general. While positive scores

[2]The full dataset was used in this step as a post-hoc analysis for feature importance.

TABLE 2.7
Tabulation of the most significant features in each of the multi-faceted predictive models.

	Positive Scale			Negative Scale	
	Top Predictive Features	Δr		Top Predictive Features	Δr
1	power words	$+0.406$	1	self-repair edits	$+0.330$
2	perceptual processing words	$+0.336$	2	time words	$+0.262$
3	perplexity	$+0.046$	3	self-repair restarts	$+0.239$

were significantly predicted by lexical categories, negative scores were more significantly predicted by self-repairs. This may suggest that individuals with high negative scores have more difficulty in communication, while individuals with high positive scores are more characterized by what they speak about.

2.6 Discussion and Conclusions

Most psychiatric disorders are diagnosed with significant clinical evaluation of an individual's abnormalities in behavior patterns, but the complexity of the many ways these disorders can manifest can limit this evaluation. Multimodal behavior analysis systems have the potential to fill this gap, but limited work has focused on the computational analysis of spoken language, despite psychological evidence for its pertinence. The present analysis approached language in three facets — through lexical, structural, and disfluency perspectives — and exposed a series of exciting results within each category as well as within interactions between them.

Words of power are heavily associated with positive symptom severity. Power words, such as *superiority*, *important*, and *exploit*, emerged as significantly predictive of positive symptom severity. The most characteristic symptoms of the positive scale involve delusions and grandiosity, which are defined by unfounded and exaggerated self-opinion and convictions of superiority, so the capability to detect these symptoms through language use is critical. Furthermore, the proportion of words of power used by an individual was the feature providing the most

influence in a predictive model for positive symptom severity, above all other features.

Lack of relative language is highly indicative of more severe psychotic symptoms. Although much work has identified reality monitoring as a particular difficulty for individuals with psychotic disorders, little to no work has examined how this difficulty might be reflected in language use. Our analyses revealed that a lack of contextual language — relative words such as *yesterday*, *lately*, and *nearby* — is highly predictive of both positive and negative symptom severity. The fewer of these words an individual uses, the more severe their psychotic symptoms in general.

Linguistic difficulty during cognitive processing can be related to negative symptom severity. Although speaking in cognitive processing terms does not strictly indicate negative symptom severity, the higher an individual's negative symptom score, the more they will self-repair (and specifically edit their language) while speaking in cognitive processing terms. This behavior is often indicative of hesitation while constructing the sentences, so it may be representative of the cognitive difficulties characteristic of the negative psychotic symptom scale.

Future work will delve into more symptom-specific analyses, as each of the positive and negative scales are subdivided into measures of seven different symptom items. Augmenting these analyses with those of audiovisual modalities also holds great promise for improving the explanatory power of these models. Through these analyses, we can achieve an even more nuanced characterization of psychotic disorders, which will constitute a significant step toward the design of future multimodal clinical decision support tools for computational phenotyping of mental illness.

Acknowledgments

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Chapter 3

Nonverbal Behavior Dynamics

Many of the essential clues to the psychiatric condition of an individual lie within the nonverbal and communicative behavior patterns they express during social interactions. The analysis described in this chapter examines quantified patterns of gaze aversion across a set of individuals recently admitted to an inpatient psychotic disorder unit at a major psychiatric hospital. These patterns are used to inform the development of discriminative models with the task of predicting schizophrenic symptom severity from both a typological and a dimensional assessment perspective. The results expose a novel set of gaze aversion behaviors distinguishing between positive subtype schizophrenia, characterized by excessive behaviors such as hallucinations and grandiosity, and negative subtype schizophrenia, characterized by diminished behaviors such as blunted affect and emotional withdrawal.

The work described in this chapter first appeared in the following publication:

> Alexandria K. Vail, Elizabeth Liebson, Justin T. Baker, Louis-Philippe Morency. Visual Attention in Schizophrenia: Eye Contact and Gaze Aversion during Clinical Interactions. *Proceedings of the Seventh International Conference on Affective Computing and Intelligent Interaction (ACII 2017)*, San Antonio, Texas, 2017.
>
> https://doi.org/10.1109/ACII.2017.8273644

3.1 Overview

When assessing the psychiatric condition of an individual, medical professionals often rely on a subjective assessment of abnormality in nonverbal and communicative behaviors during clinical interviews and day-to-day interactions. Although expert clinicians have a lifetime of experience and knowledge from which to draw a diagnosis, accurate judgment of individual cases is often inhibited by time constraints, clinician fatigue, or merely the human inability to judge every dimension of a person's condition at once. These limitations can interfere with determining the most accurate and timely diagnosis, and by extension the most effective plan of treatment.

One approach to addressing this challenge is to augment the assessment of these medical professionals with tools that can provide objective, automated analysis of a person's behaviors during these focused interactions. These systems would be capable of evaluating behavior patterns regarding previously collected data of the same individual (perhaps despite changing clinicians), in addition to the information gained from a wider demographic set of individuals carrying similar diagnoses. Such a tool could offer more detailed insight into a person's psychiatric condition, allowing the attending clinician to reach a better-informed diagnosis.

In everyday interaction, eye contact is widely considered to be an important signifier of aggression, social rapport, confidence, or interest; on the other hand, the lack of eye contact is often considered an indicator of respect, submissiveness, or even anxiety [113]. As a result, abnormal patterns in eye contact and gaze aversion behaviors are often adopted as significant indicators of psychiatric disorders [189]. Unusual behavior in this space is often a critical indicator of psychiatric illness, most notably in anxiety, depression, and cases of high suicidality [20, 206].

In this chapter, we present a detailed investigation of eye gaze behaviors for patients with schizophrenic symptoms. Our analysis focuses on identifying behavior markers differentiating two subtypes of schizophrenia: positive subtype and negative subtype [107]. These subtypes of schizophrenia have been shown to respond differently to a variety of treatment plans [186] and exhibit different predispositions to comorbid conditions [149]. These findings motivate our

analysis, since they suggest that correct identification of schizophrenic subtype is critical to determining the appropriate course of treatment for a given individual. We analyze eye gaze patterns in the context of the patient's facial expressions, as well as the dialogue cues from the clinician. In the later part of this chapter, our detailed analysis will inform the development of predictive models for schizophrenic subtypes (i.e., typological assessment) and for continuous symptom severity (i.e., dimensional assessment).

3.2 Related Work

Many psychiatric disorders cause disruption in the normal function of nonverbal or communicative behaviors of an individual [20, 88]. In particular, multiple studies have suggested the importance of identifying gaze aversion in depression and cases of high suicidality; individuals with depression are suggested to fixate more frequently [88] and maintain significantly less eye contact when speaking with an interviewer [206] than those without. An avoidance of eye contact has also been seen in individuals diagnosed with other adverse clinical states, such as attention deficit disorder or autism [207].

Some studies have suggested particular differences in gaze behavior in individuals diagnosed with schizophrenia. Rutter suggested that many of these individuals are behaviorally indistinguishable from the general population during conversations of no personal importance, but display markedly abnormal gaze aversion patterns when asked to speak about personal matters [175]. Bergman et al. supported this finding, and suggested that in these afflicted individuals, much of the nonverbal behavior expressed does not synchronize with the verbal utterances [20]. Interestingly, in this study a lack of eye contact was not only observed in the case of the diagnosed person, but in the interviewing clinician as well. Laing suggests that persons diagnosed with schizophrenia may feel particularly vulnerable or exposed under the gaze of others, and may actively avoid eye contact as a result [124]. The present analysis uses this to inform 'categories' of interview questions (see Section 3.3).

Our work examines a variety of gaze aversion behaviors regarding an individual's results on a clinical inventory of schizophrenic symptoms. Section 3.3 continues with a detailed description of the interview dataset and the various feature extractions performed upon it. Section 3.4 describes a set of hypothesis-driven experiments, which informed a predictive analysis described in Section 3.5. We interpret some significant features identified in Section 3.6. The report concludes with a brief overview and some thoughts toward future directions in Section 3.7.

3.3 Clinical Interview Dataset

The data used in this chapter originate from the same audiovisual recordings described in Chapter 2. This dataset consists of a series of clinical interviews with adult individuals recently admitted to an inpatient psychotic disorder unit at McLean Hospital, a major psychiatric facility. Video and audio recordings were collected from 21 unique participants (six of whom were female). Each session involved a semi-structured clinical interview between the admitted individual and a clinician, lasting approximately 10–15 minutes each. The interview script was modeled upon existing everyday clinical interactions designed to elicit reactions that may be illustrative of the psychiatric condition of the individual.[1] A list of interview questions is presented in Table 3.1.

Following the conclusion of each interview, the participant was administered a series of clinical scales, including the Positive and Negative Syndrome Scale (PANSS) [107], a scale used for measuring schizophrenic symptom severity. PANSS involves seven-point ratings of 30 symptoms across three dimensions: *positive symptoms*, involving behaviors in excess or distortion of normal function, *negative symptoms*, involving behaviors diminished or suppressed below normal function, and *general psychiatric symptoms*, involving items that cannot be linked decisively to either syndrome. Items from the Positive and Negative scales are listed and described in Table 3.2.

[1] Although participants varied in previous exposure to similar interactions, this diversity is reflective of the larger population, and we believe that this strengthens the applicability of this analysis.

FIGURE 3.1
Example set of annotated gaze direction labels for sample video frames.

Participants are grouped by their PANSS *composite score*, defined as the difference between the positive and negative symptom scores [107]. Participants with a composite score above zero are classified as having *positive subtype* schizophrenia, whereas those below or equal to zero were classified as having *negative subtype* schizophrenia. Twelve of the participants are classified as expressing positive subtype schizophrenic symptoms, and nine are classified as expressing negative subtype. The average Positive Scale score in the present sample is $M = 17.48$ ($SD = 8.09$) and Negative Scale $M = 13.95$ ($SD = 3.92$), both in a possible range of 7 to 49; the average composite score is $M = 3.52$ ($SD = 9.35$), in a possible range of -42 to 42.

Gaze Aversion Annotation

Each session video was manually annotated for gaze behavior. This annotation task was conducted in two stages: annotation of lateral gaze direction and annotation of vertical gaze direction. Lateral gaze direction was manually classified into *left*, *center*, or *right*; similarly, vertical direction into *up*, *center*, or *down*. Note that an annotation of (*center*, *center*) would indicate gaze at the interviewing clinician and *left* and *right* are directions from the perspective of the interviewing clinician. When eye gaze direction was conflated with head gaze direction, the 'absolute' direction of aversion was taken. For an illustration of sample labels from this annotation scheme, see Figure 3.1.

To evaluate the reliability of this annotation scheme, a second annotator repeated this pro-

cedure on eight sessions (approximately 38% of the dataset). Each session was segmented by the tenth of a second, and inter-annotator agreement was calculated based on classification into each of the three directional states for each dimension. This resulted in a Krippendorff's alpha coefficient of $\alpha = 0.89$ for lateral movement and $\alpha = 0.76$ for vertical movement, each of which exceeds the usual threshold for a 'reliable' level of agreement [121].

Dialogue Annotations

Interview items were grouped into two distinct categories: *introspective questions*, in which the participant is asked to examine their thoughts, feelings, or mental state, and *extrospective questions*, in which the participant is asked to describe the state of their environment. Inter-annotator agreement across four independent annotators achieved a Krippendorff's alpha coefficient of $\alpha = 0.85$, a 'reliable' level of agreement [121]. This classification is presented in Table 3.1.

Annotation of interview dialogue involved selection of the moment at which each question segment began, accurate to the tenth of a second, as well as the classification of the question itself into one of thirteen questions types (see Table 3.1). To evaluate inter-annotator agreement, a second annotator repeated this procedure on five sessions (approximately 24% of the dataset). On average, there was a difference of 1.2 seconds regarding annotation of the start of a question. There were two instances of 'missed' question annotations and one instance of disagreement on question classification, out of a total of 48.

Facial Expression Feature Extraction

Facial expression for the current analysis is defined in terms of the Facial Action Coding System (FACS), a procedure designed to describe facial expression systematically via individual muscle movements [53]. Video recordings of both clinician and participant were collected at a resolution of 1280×960 pixels at 30 frames per second. Facial action unit intensities were extracted from these videos using OpenFace, a state-of-the-art open-source facial behavior analysis toolkit [15].

TABLE 3.1
Classification of interview protocol items into introspective questions and extrospective questions.

Introspective Questions	Extrospective Questions
Has anything in particular been on your mind?	What brought you into the hospital?
What are your goals for the hospitalization?	What has the team here been helping you with?
How is your mood/spirits?	Would you say that they are doing a good job?
How is your thinking/focus?	How have people been treating you?
How is your self-confidence compared to how it usually is?	How is the food?
What changes do you observe since you were hospitalized?	How is your energy?
	How have you been sleeping?

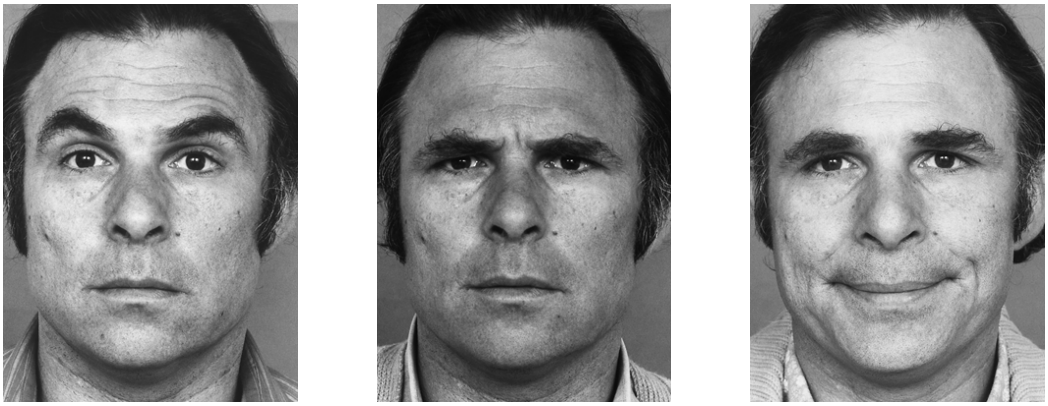
After processing with OpenFace, each frame of the video receives an intensity score $s_i \in [0, 5]$ for each of 17 facial action units, four of which are used in the present analysis. Frames with less than 70% confidence in the facial landmark detection results (often due to extreme head pose, rapid motion, or occlusion) were discarded. This threshold resulted in elimination of approximately 16% of the recorded video frames. The three facial action units most prominent in the present analysis are illustrated in Figure 3.2.

3.4 Statistical Analysis

Initial examination of the recorded interviews resulted in several qualitative observations, which informed the definition of hypotheses detailed in the following subsections. Each of these hypotheses were compared using the appropriate statistical models. Tests for normality and homoscedascity were performed before each test, and all reported p-values have been corrected using the Benjamini-Hochberg procedure for controlling the family-wise error rate within each hypothesis group. In the first section, we study overall differences in aversion behavior. The next section studies differences when contextualized within dialogue events, and the final section studies the interactions with facial expressions.

TABLE 3.2
Enumeration and brief description of a selection of symptoms contained in the PANSS positive and negative scales [107].

Scale Item	Brief Description of Behavior
Positive Scale	
Delusions	Beliefs which are unfounded, unrealistic, and idiosyncratic.
Conceptual Disorganization	Disorganized process of thinking characterized by disruption of goal-directed sequencing, e.g., circumstantiality, tangentiality, loose associations, non-sequiturs, gross illogicality, or thought block.
Hallucinatory Behavior	Verbal report or behavior indicating perceptions which are not generated by external stimuli. These may occur in the auditory, visual, olfactory, or somatic realms.
Grandiosity	Exaggerated self-opinion and unrealistic convictions of superiority, including delusions of extraordinary abilities, wealth, knowledge, fame, power, and moral righteousness.
Hostility	Verbal and nonverbal expressions of anger and resentment, including sarcasm, passive-aggressive behavior, verbal abuse, and assaultiveness.
Negative Scale	
Blunted Affect	Diminished emotional responsiveness as characterized by a reduction in facial expression, modulation of feelings, and communicative gestures.
Emotional Withdrawal	Lack of interest in, involvement with, and affective commitment to life's events.
Poor Rapport	Lack of interpersonal empathy, openness in conversation, and sense of closeness, interest, or involvement with the interviewer. This is evidenced by interpersonal distancing and reduced verbal and nonverbal communication.
Difficulty in Abstract Thinking	Impairment in the use of the abstract-symbolic mode of thinking, as evidenced by difficulty in classification, forming generalizations, and proceeding beyond concrete or egocentric thinking in problem-solving tasks.
Lack of Spontaneity and Flow of Conversation	Reduction in the normal flow of communication associated with apathy, avolition, defensiveness, or cognitive deficit. This is manifested by diminished fluidity and productivity of the verbal-interactional process.



(A) AU2 OUTER BROW RAISER (B) AU4 BROW LOWERER (C) AU14 DIMPLER

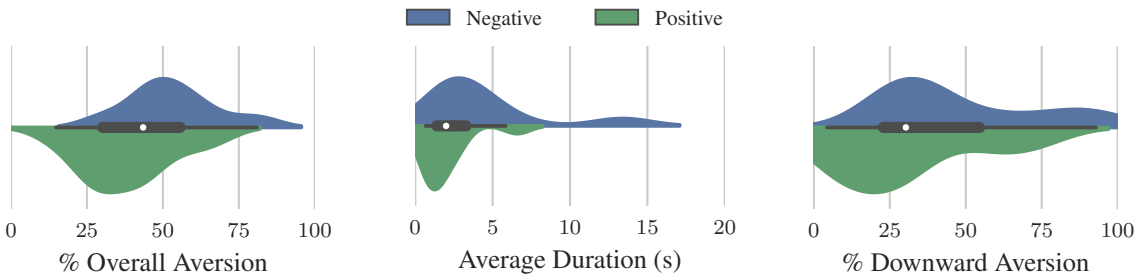
FIGURE 3.2
Illustration of the subset of facial action units used in the present analysis [53].

Aversion

The first set of hypotheses tested involved general trends in gaze aversion behaviors between individuals expressing positive and negative subtype schizophrenia.

H1.1. *Individuals expressing positive subtype schizophrenia avert their gaze less than those expressing negative subtype schizophrenia.* The first hypothesis examines the raw percentage of the interview in which participants are not averting their gaze from the interviewing clinician. This hypothesis is grounded in the understanding that individuals scoring highly on the positive symptom scale express such symptoms as hostility and suspiciousness, which may result in less gaze aversion. There was a statistically significant difference between groups at the 95% confidence level as determined by a one-way ANOVA [$F(1, 19) = 5.049$, $p = 0.037$] (see Figure 3.3a). A post-hoc comparison indicated that the average percentage of aversion over the session for individuals expressing positive subtype ($M = 38.34\%$, $SD = 14.86\%$) was significantly smaller than the average percentage for individuals expressing negative subtype ($M = 52.94\%$, $SD = 14.57\%$). This result suggests that individuals expressing positive subtype schizophrenia avert their gaze less often, in general, than individuals expressing negative subtype schizophrenia.

H1.2. *Individuals expressing negative subtype schizophrenia avert their gaze for longer pe-*



(A) H1.1. Percentage of the interview in which gaze was averted. [$F(1, 19) = 5.049$, $p = 0.037$]

(B) H1.2. Average duration of an aversion (in seconds). [$H(1) = 5.838$, $p = 0.016$]

(C) H1.5. Percentage of aversions that were (non-exclusively) downward. [$H(1) = 2.909$, $p = 0.088$]

FIGURE 3.3
Illustration of a selection of the distributions most significantly different between participants expressing positive- versus negative-subtype schizophrenic symptoms. As some distributions fail normality tests, we illustrate using the violin plot, an alternative to the traditional box plot that also accurately represents the distribution of the data using smoothed density plots. The center line represents the median and interquartile range of the dataset, much like a traditional box plot.

riods of time than individuals expressing positive subtype schizophrenia. The second hypothesis examines the average temporal length of gaze aversions when they do occur. This hypothesis is based on the defining features of negative symptoms such as poor rapport and social withdrawal, which may suggest more consistent aversion behavior. There was a statistically significant difference between groups at the 95% confidence level as determined by a Kruskal-Wallis H-test[2] [$H(1) = 5.838$, $p = 0.016$] (see Figure 3.3b). A post-hoc comparison indicated that the average aversion duration for individuals expressing positive subtype schizophrenia ($M = 1.93$s, $SD = 1.63$s) was significantly smaller than for individuals expressing negative subtype ($M = 4.23$s, $SD = 3.69$s). This result suggests that when individuals expressing negative subtype schizophrenia avert their gaze, they are likely to do so for a longer period of time than individuals expressing positive subtype.

H1.3. *Individuals expressing positive subtype schizophrenia cover larger area during aversions than individuals expressing negative subtype schizophrenia.* The third hypothesis examines the average distance covered during gaze aversions. This hypothesis is based on the suggestion

[2]Both distributions failed a Shapiro-Wilk test for normality: positive subtype [$W(12) = 0.705$, $p = 0.001$] and negative subtype [$W(9) = 0.705$, $p = 0.002$].

that positive subtype schizophrenia involves a degree of hyperactivity and excitement, lending to fewer gaze fixations. To operationalize this definition, for each aversion event, each two-dimensional directional annotation is treated as a point in $\{-1, 0, +1\}^2$-space, and the Euclidean distance $\|\boldsymbol{x_i} - \boldsymbol{x_{i+1}}\|$ is calculated between every pair of consecutive points $\boldsymbol{x_i}$ and $\boldsymbol{x_{i+1}}$ along the aversion path. The sum of these distances results in a measure of the distance covered over the course of the aversion. There was *not* a statistically significant difference between groups at the 95% confidence level as determined by a Kruskal-Wallis H-test[3] [$H(1) = 1.823$, $p = 0.177$].

H1.4. *Individuals expressing positive subtype schizophrenia are more likely to avert their gaze laterally than individuals expressing negative subtype schizophrenia.* The fourth hypothesis examines the proportion of aversions that are (non-exclusively) lateral. Vertical aversions are often associated with anxiety, which is more canonically associated with the social withdrawal and poor rapport of negative subtype schizophrenia. There was *not* a statistically significant difference between groups at the 95% confidence level as determined by a Kruskal-Wallis H-test[4] [$H(1) = 1.548$, $p = 0.213$].

H1.5. *Individuals expressing negative subtype schizophrenia are more likely to avert their gaze downward than individuals expressing positive subtype schizophrenia.* The final hypothesis examines the proportion of aversions that are (non-exclusively) downward. Downward aversions have previously been suggested to be significantly indicative of individuals diagnosed with depression [88], which is often associated with many negative schizophrenic symptoms. There was *not* a statistically significant difference between groups at the 95% confidence level as determined by a Kruskal-Wallis H-test[5] [$H(1) = 2.909$, $p = 0.088$] (see Figure 3.3c).

[3]Both distributions failed a Shapiro-Wilk test for normality: positive subtype [$W(12) = 0.855$, $p = 0.043$] and negative subtype [$W(9) = 0.822$, $p = 0.036$].

[4]The positive subtype distribution failed a Shapiro-Wilk test for normality [$W(12) = 0.598$, $p = 0.000$].

[5]The negative subtype distribution failed a Shapiro-Wilk test for normality [$W(9) = 0.814$, $p = 0.029$].

Aversion and Dialogue

The second set of hypotheses tested involves eye contact and gaze aversion as related to dialogue and question types (see Section 3.3 for details).

H2.1. *Introspective questions result in more gaze aversion than extrospective questions.* The first hypothesis examines the difference in gaze aversion during introspective and extrospective questions. Introspective questions involve evaluating intimate details about the self, which often induces discomfort or unease. There was a statistically significant difference within subjects as determined by an ANOVA with repeated measures [$F(1, 20) = 7.347$, $p = 0.013$]. A post-hoc comparison indicated that the average proportion of aversion during introspective questions ($M = 53.70\%$, $SD = 21.21\%$) was significantly more than during extrospective questions ($M = 49.89\%$, $SD = 17.78\%$). This result suggests that regardless of subtype, individuals expressing schizophrenia are more likely to avert their gaze during introspective questions than during extrospective questions.

H2.2. *Individuals expressing negative subtype schizophrenia avert their gaze more often during introspective questions than individuals expressing positive subtype schizophrenia.* The second hypothesis suggests that individuals expressing negative subtype schizophrenia would avert their gaze more frequently during introspective questions than their positive subtype counterparts. This was informed by the prominent negative scale item involving difficulty in abstract thinking, which may result in difficulty answering this type of interview question. There was a statistically significant difference between groups as determined by a one-way ANCOVA while controlling for overall aversion percentage [$F(1, 18) = 6.486$, $p = 0.020$]. A post-hoc comparison indicated that the average proportion of aversion during introspective questions for individuals expressing positive subtype schizophrenia ($M = 41.33\%$, $SD = 13.66\%$) was significantly less than for individuals expressing negative subtype ($M = 61.81\%$, $SD = 16.12\%$). This result suggests that individuals expressing negative subtype schizophrenia are more likely to avert their gaze during introspective questions than individuals expressing positive subtype schizophrenia.

Aversion and Facial Expression

The final set of hypotheses examines the facial expressions conveyed during gaze aversions (see Section 3.3).

H3.1. *When averting gaze, individuals expressing positive subtype schizophrenia express more* AU2 OUTER BROW RAISER *than individuals expressing negative subtype schizophrenia.* The first hypothesis examines the average expression of AU2 OUTER BROW RAISER during gaze aversions. Brow raising is often associated with fear, surprise, and other spontaneous emotions [53], which may be more present in individuals expressing positive symptoms such as excitement and hyperactivity. There was a statistically significant difference between groups as determined by a one-way ANCOVA while controlling for average overall AU2 intensity [$F(1, 18) = 5.627$, $p = 0.029$]. A post-hoc comparison indicated that the average AU2 intensity expressed during aversion for individuals expressing positive subtype schizophrenia ($M = 0.847$, $SD = 0.316$) was significantly greater than for individuals expressing negative subtype ($M = 0.757$, $SD = 0.266$). This result suggests that individuals expressing positive subtype schizophrenia tend to express AU2 OUTER BROW RAISER when they avert their gaze more than individuals expressing negative subtype schizophrenia.

H3.2. *When averting their gaze, individuals expressing negative subtype schizophrenia express more* AU4 BROW LOWERER *than individuals expressing positive subtype schizophrenia.* The second hypothesis examines the average expression of AU4 BROW LOWERER during gaze aversions. Brow lowering is an expression canonically associated with negative emotions [53], which may be more present in individuals expressing negative subtype schizophrenic symptoms. There was a statistically significant difference between groups as determined by a one-way ANCOVA while controlling for average overall AU4 intensity [$F(1, 18) = 5.643$, $p = 0.029$]. A post-hoc comparison indicated that the average AU4 intensity expressed during aversion for individuals expressing negative subtype schizophrenia ($M = 0.125$, $SD = 0.053$) was significantly greater than for individuals expressing positive subtype ($M = 0.057$, $SD = 0.047$). This re-

sult suggests that individuals expressing negative subtype schizophrenia tend to express AU4 BROW LOWERER when they avert their gaze more than individuals expressing positive subtype schizophrenia. Prior work on individuals expressing schizophrenia without regard to subtype has identified this expression as generally indicative of schizophrenia [120], so the suggestion that this facial expression is expressed differently between subtypes is notable.

H3.3. *When averting their gaze, individuals expressing negative subtype schizophrenia express more* AU14 DIMPLER *than individuals expressing positive subtype schizophrenia.* The third hypothesis examines the average expression of AU14 DIMPLER during gaze aversions. AU14 DIMPLER is often associated with contempt, which may be more prevalent in individuals expressing negative subtype schizophrenia than those expressing positive subtype. There was *not* a statistically significant difference between groups as determined by a one-way ANCOVA while controlling for average overall AU14 intensity [$F(1, 18) = 3.922$, $p = 0.063$].

H3.4. *When averting their gaze, individuals expressing negative subtype schizophrenia express more* AU20 LIP STRETCHER *than individuals expressing positive subtype schizophrenia.* The final hypothesis examines the average expression of AU20 LIP STRETCHER during gaze aversions. AU20 is often likened to a 'grimace' of the face, which occurs relatively infrequently in social interaction, but prior work has suggested a particular aversion to 'negative affect' facial expressions in schizophrenia [141]. There was *not* a statistically significant difference between groups as determined by a one-way ANCOVA while controlling for average overall AU20 intensity [$F(1, 18) = 0.165$, $p = 0.689$].

3.5 Predictive Models

To approach prediction of schizophrenic symptom severity from both a typological and a dimensional assessment perspective, two sets of computational models were built. The first analysis approaches the typological perspective, with the target of predicting an individual's schizophrenic subtype based on gaze aversion behavior descriptors. The second analysis addresses the dimen-

sional perspective, using these gaze aversion behavior descriptors to predict quantitative scores on the PANSS inventory [107].

Computational Descriptors

Based on the results of the statistical analyses conducted previously, a series of thirteen behavior descriptors were extracted from each interview session. This set of descriptors was provided as a set of features to both the typological and the dimensional predictive analyses.

Gaze aversion percentage. Over the course of the entire interview session, the percentage of time in which the participant averted their gaze from the interviewing clinician.

Gaze aversion percentage (introspective). Over the course of all introspective question segments (see Section 3.3), the percentage of time in which the participant averted their gaze from the interviewing clinician.

Aversion duration. Across the set of all aversion events, the average temporal duration of a gaze aversion.

Aversion distance. Across the set of all aversion events, the average distance covered in an aversion (see Section 3.4, H1.3. for operational definition). This allows for the distinction between fixation and gaze-wandering.

Lateral/vertical aversion percentage. (2 features) Across the set of all aversion events, the percentage of events in which the participant made a lateral/vertical aversion. A lateral/vertical aversion is an event in which the participant's gaze drifts (non-exclusively) laterally/vertically from direct gaze toward the interviewing clinician.

Directional aversion percentage. (4 features) Across the set of all aversion events, the percentage of events in which the participant made an aversion in one of the four cardinal directions: left, right, up, or down. A directional aversion is an event in which the participant's gaze drifts (non-exclusively) in that direction relative to direct gaze toward the interviewing clinician.

TABLE 3.3
Typological experiments. Performance of the automatically validated SVM classification model in terms of accuracy, Krippendorff's α, and F_1 score, as compared to a majority-class predictor baseline model.

Model	Accuracy	Krippendorff's α	F_1 Score
SVM	76.19%	0.5309	0.7597
Baseline	57.14%	−0.2424	0.3636

Average AU2 intensity during aversion. Across all aversion events, the average expressed intensity of AU2 OUTER BROW RAISER (see Figure 3.2a).

Average AU4 intensity during aversion. Across all aversion events, the average expressed intensity of AU4 BROW LOWERER (see Figure 3.2b).

Average AU14 intensity during aversion. Across all aversion events, the average expressed intensity of AU14 DIMPLER (see Figure 3.2c).

Typological Assessment

The typological assessment is framed as a classification problem in which the target class value is either positive or negative subtype (see Section 3.3). A set of support vector machine (SVM) classifiers [50] were trained for this task using leave-one-person-out cross-testing, following leave-one-person-out cross-validation for hyperparameter tuning and feature selection using logistic regression [204]. Models were validated upon Krippendorff's α. The model was allowed to take on either a linear kernel $K(\boldsymbol{x}, \boldsymbol{x'}) = \boldsymbol{x}^T\boldsymbol{x'}$ or a Gaussian radial basis function (RBF) kernel $K(\boldsymbol{x}, \boldsymbol{x'}) = \exp(-\gamma\|\boldsymbol{x} - \boldsymbol{x'}\|^2)$, for any two feature vectors $\boldsymbol{x}, \boldsymbol{x'} \in \mathbb{R}^9$. Hyperparameters validated include $C \in \{10^{-5}, 10^{-4}, \ldots, 10^4\}$ and, in the case of the Gaussian-RBF kernel, $\gamma \in \{0.00, 0.05, \ldots, 1.00\}$.

Performance of cross-testing in terms of accuracy, Krippendorff's α, and F_1 score is displayed in Table 3.3, alongside a baseline majority-class predictor. This classification model achieved a performance well above the majority-class baseline during cross-testing. Although the Krippendorff's α does not reach a 'reliable' level of agreement [121], the moderate level of performance

TABLE 3.4
Dimensional experiments. Performance of the automatically validated ϵ-SVR regression models in terms of Pearson's r.

Model	Pearson's r	p
Positive Score	0.5853	0.005
Negative Score	0.4330	0.049
Composite Score	0.5714	0.006

achieved does suggest the existence of significant information regarding the identification of schizophrenic subtype in an individual's gaze aversion behaviors.

Dimensional Assessment

The second task of dimensional assessment is framed as a regression problem in which the target class value is either the individual's total Positive Scale score (values 7 to 49), the individual's total Negative Scale score (values 7 to 49), or the individual's composite score (values -42 to 42). A series of ϵ-support vector regressors (ϵ-SVRs; [50]) were trained for this task using leave-one-person-out cross-testing, following leave-one-person-out cross-validation for hyperparameter tuning and feature selection using LASSO [193]. Models were optimized upon Pearson's r. The model was validated upon the same hyperparameters specified in Section 3.5; in addition, the range parameter ϵ was validated within $\epsilon \in \{10^{-5}, 10^{-4}, \ldots, 10^{-1}\}$.

Performance of the best-performing regression models in terms of Pearson's r is displayed in Table 3.4. All three models were able to achieve a reasonable level of correlation with true PANSS scores during cross-testing. All of these correlations were statistically significant at the 95% confidence level. Prediction of raw dimensional scores is a more complex task than prediction of coarse typological subtype, but the promising results achieved reinforce the proposition that gaze aversion behavior is a prominent social signal containing information relevant to the identification of schizophrenic symptom severity.

3.6 Behavior Analysis

The final stage of this analysis examines one of the predictive models in detail, identifying and interpreting the significance of the most influential features. For this final step, a LASSO linear model [193] was trained upon the entire dataset, optimizing performance on composite score prediction in terms of Pearson's r. The model was limited to a selection of five features that best predicted the PANSS composite score of the participants. The LASSO model achieved a Pearson's $r = 0.65$ on the training set (compare to model performance in Section 3.5; note that this is performance on the training set, rather than leave-one-person-out validation). We review the five features selected; the model is presented in Table 3.5.

Gaze aversion during introspective questions. The most influential feature selected is the percentage of introspective question segments in which the individual is averting their gaze from the clinician. The more the participant averts their gaze during introspective questions, the lower their composite score tends to be, and by extension, the more negative symptoms they tend to express. This result was mirrored in Section 3.4, where there existed a statistically significant difference in aversion during introspective questions between individuals expressing positive subtype and negative subtype schizophrenic symptoms.

Average intensity of AU4 BROW LOWERER during gaze aversion. The next feature selected is the average intensity of AU4 BROW LOWERER (see Figure 3.2b) during aversion events. The more intense the average brow lowering during gaze aversion, the lower the participant's composite score tends to be, and the more negative symptoms they tend to express. This result was also mirrored in Section 3.4, where there existed a statistically significant difference in AU4 expression during aversion events between individuals expressing positive and negative symptoms.

Proportion of lateral gaze aversion. The only positively correlated feature selected is the proportion of gaze aversions that were (non-exclusively) lateral aversions. The more gaze aversions in which the participant's gaze moves laterally, the higher their composite score tends to

TABLE 3.5
Features selected by a LASSO linear model, when limited to five features, predicting the PANSS composite score of the participant.

PANSS Composite Score =
$-8.374 \times$ Gaze aversion during introspective questions
$-4.760 \times$ Average intensity of AU4 during gaze aversion
$+1.972 \times$ Proportion of lateral gaze aversion
$-0.725 \times$ Proportion of downward gaze aversion
$-0.001 \times$ Average gaze aversion duration
Pearson's $r = 0.653$, $p = 0.002$

be, and the more positive symptoms they tend to express. Interestingly, this descriptor was *not* discriminative on its own in the statistical analyses in Section 3.4. This may suggest that it holds more discriminative information when combined with these other features.

Proportion of downward gaze aversion. The next feature selected is the proportion of gaze aversions that were (non-exclusively) downward aversions. The more gaze aversions in which the person looks downward, the lower their composite score tends to be, and the more negative symptoms they tend to express. This descriptor was also not considered a discriminative feature in the statistical analyses in Section 3.4, although it was more significant than lateral aversion.

Average gaze aversion duration. The final feature included, with relatively little influence, is the average length of time of an aversion event. The longer periods of time a person averts their gaze, the lower their composite score tends to be, and the more negative symptoms they tend to express. Although this descriptor was significantly discriminative between individuals expressing positive and negative subtype symptoms in Section 3.4, it was not very influential in this model; this may suggest that, although this feature is still discriminative, the prior features explain the difference more accurately than gaze aversion duration.

3.7 Conclusion

Most psychiatric disorders are diagnosed with significant clinical evaluation of an individual's nonverbal and communicative behavior patterns. The present analysis aims to develop classifier models that can accurately differentiate between subtypes of schizophrenic symptoms based on the patterns of eye contact and gaze aversion expressed by an individual during a clinical interview. A strength of this work is the approach to these behaviors through an investigation of symptom severity rather than coarse-grained diagnoses; since many symptoms are shared across comorbid conditions, this work can inform systems developed toward more personalized symptom-based care.

Statistical comparisons suggest a few interesting differences in behavior between positive and negative symptoms of schizophrenia. In general, individuals expressing negative-subtype schizophrenic symptoms tend to avert their gaze from the clinician more and for longer periods of time, and this difference is even more notable during introspective questions. When these individuals do avert their gaze, they tend to lower their brows (AU4 BROW LOWERER) more than individuals expressing positive symptoms.

We have reported a predictive model able to distinguish between positive and negative subtype expressing individuals with reliable performance based on gaze aversion behaviors during a clinical interview. In addition, predictive models can reasonably predict PANSS numeric scores on the Positive Scale and the Negative Scale, as well as the composite difference score. We identify the most influential behavior descriptors and potential interactions between them; most notably, the direction of gaze aversion becomes a discriminative feature when taken in concert with other descriptors. By approaching computational identification of schizophrenic symptom intensity from both a typological and dimensional perspective, this line of work constitutes a promising step in the development of technologies to aid clinicians in diagnosis of psychiatric illnesses.

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Part II

Social Behavior

"To say that the human being behaves individually at one moment and socially at another is as absurd as to declare that matter follows the laws of chemistry at a certain time and succumbs to the supposedly different laws of atomic physics at another..."

– Edward Sapir, 1927 [177]

Chapter 4

Conversational Turn-Taking

Clients may terminate therapy for various reasons, but one of the most common causes is the lack of a strong working alliance. The concept of working alliance captures the collaborative relationship between a client and their therapist when working toward the progress and recovery of the client seeking treatment. In this chapter, we demonstrate that analysis of the facilitative behaviors that the participants use throughout the interaction may aid in identifying a weak working alliance before early client dropout. The work in this chapter focuses on the head gestures of both the client and therapist, contextualized within conversational turn-taking actions between the pair during psychotherapy sessions. We identify multiple behavior patterns suggestive of an individual's perspective on the working alliance; interestingly, these patterns also differ between the client and the therapist. These patterns inform the development of predictive models for self-reported ratings of working alliance, which demonstrate significant predictive power for both client and therapist ratings.

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>
> https://doi.org/10.1109/FG52635.2021.9667021

4.1 Overview

Previous research has established that the strength of the relationship between a client and their therapist is a robust predictor of positive therapy outcomes [18, 92, 135]. Much of the current psychological literature on the client-therapist relationship pays particular attention to what is known as the *working alliance*. Although many variations on the definition of 'working alliance' can be found, there is a consensus on the central idea that the working alliance captures the *collaborative* aspect of the therapist-client relationship [23, 92]. Higher therapist-reported and especially client-reported ratings of the working alliance have been strongly associated with reduction of the client's symptoms and concerns [62, 91, 92], but also with other positive therapy outcomes such as reduced drug abuse and recidivism [132] and improved medication compliance [59]. Of particular note is the recognized relationship between the strength of the working alliance and client dropout [59, 118, 178]. Proactive detection is especially valuable in this case: by the time a client has decided to quit therapy, the time for potential intervention has already passed. Understanding the complexity of the therapist-client relationship is crucial for informed treatment decision-making.

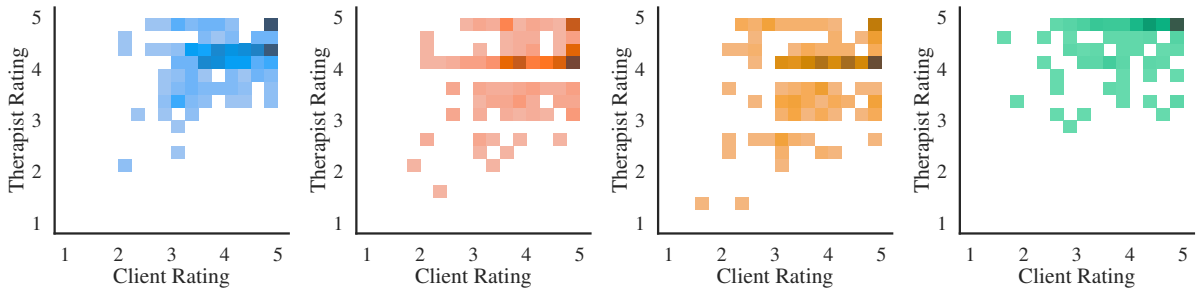
Unfortunately, measuring the strength of a working alliance faces several challenges. Most recorded ratings of the working alliance are obtained by self-reports from the client and their therapist, who are also participants in the interaction; previous research has documented significant divergences in these two participants' perception of the working alliance. Clients are often hesitant to express feedback or concerns [165, 167]: many clients do not express any concern at all until they have already decided to discontinue treatment [87]. On the other hand, therapists often miss subtle signs of client discontent during therapy sessions [165]. Alarmingly, some studies have even demonstrated that therapists may perform worse than chance at identifying signs of client frustration or annoyance [86, 135]. Several attempts have been made to evaluate the reliability of third-party human observers, but to date, observer ratings of the working alliance have repeatedly emerged as the least valuable predictors of therapy outcomes [92, 135].

The primary aim of this chapter is to explore the use of computational behavior analysis to overcome the obstacles facing the objective measurement of the working alliance. Our analysis focuses primarily on head gestures and turn-taking behaviors, as these features have been identified as essential signals in the detection of similar measures of relationship [39, 73]. We begin with a set of inferential analyses to explore general trends in behavior that may indicate a participant's perception of the working alliance. Given these identified patterns, we develop a series of predictive models to estimate the working alliance ratings provided by the therapist and the client. Following this, we perform a set of ablation studies to examine the value of including specific categories of behavioral features, such as therapist behavior versus client behavior or head gesture features versus turn-taking features. Finally, we conclude by discussing some of the most notable takeaways revealed by these results and the promising directions for future work.

4.2 Related Work

To date, there has been little to no computational behavior analysis of working alliance in psychotherapy. However, there is a large volume of published studies in the computational literature that explores a similar construct: *rapport*, which can broadly be defined as mutual attentiveness, amiability, and receptivity between interaction participants [194]. Rapport differs from the working alliance in several fundamental ways, but one of the most notable differences is that rapport is generally considered to be 'other-focused', in which the primary goal is to develop a relationship between participants [194]. In contrast, the working alliance is 'task-focused', in which developing the relationship is secondary to the accomplishment of mutual goals [23]. The working alliance is more commonly described in asymmetric interactions, such as between therapist and client or teacher and student [92]. However, both concepts are related to relationship-building, and given the relative paucity of studies investigating working alliance computationally, we draw insight from the considerable amount of literature on the similar concept of rapport.

In previous studies of dyadic interaction, different behaviors have been shown to be related



(A) Overall Scores **(B)** Goal Subscale Scores **(C)** Task Subscale Scores **(D)** Bond Subscale Scores

FIGURE 4.1
Heatmap distributions of client and therapist ratings of working alliance and its subscales.

to rapport-building. One such behavior is head gestures: nodding is recognized as one of the most valuable indicators of rapport between human participants [194]. To a lesser extent, head shakes are also related to rapport in therapeutic contexts [198]. A growing body of literature has investigated the incorporation of rapport-building when designing virtual agents; gestures of both head and hands have been identified as some of the most influential behaviors for inclusion [73, 169].

Significant attention has also been paid to turn-taking behaviors in 'listening' agents [40]. Appropriate backchanneling (verbal and nonverbal) is critical to developing user trust [21]. Similarly, increased pauses have been recognized as positively impacting rapport-building, in terms of waiting to 'grab the floor' after a partner's dialogue turn but also within a turn, allowing the partner to 'grab the floor' themselves [38]. Taking longer dialogue turns — speaking for longer periods before transitioning to the partner — significantly impairs the development of rapport between participants [39]. Given that the therapeutic setting is an asymmetric interaction, 'listening' behaviors are especially pertinent in this context.

4.3 Dataset

Audiovisual recordings were collected from 266 therapy sessions between 39 unique clients and 11 unique therapists. Each therapist met with an average of 3.6 unique clients, and each client

TABLE 4.1
Sample items from both therapist and client versions of the Working Alliance Inventory.

Goal Subscale	Task Subscale	Bond Subscale
[Therapist] and I collaborate on setting goals for my therapy.	What I am doing in therapy gives me new ways of looking at my problem.	I believe [Therapist] likes me.
[Therapist] and I have established a good understanding of the kind of changes that would be good for me.	[Therapist] and I agree on what is important for me to work on.	I feel that [Therapist] appreciates me.
We are working towards mutually agreed upon goals.	[Client] and I agree about the steps to be taken to improve his/her situation.	I feel [Therapist] cares about me even when I do things that he/she does not approve of.
[Client] and I have a common perception of his/her goals.	[Client] and I both feel confident about the usefulness of our current activity in therapy.	I appreciate [Client] as a person.
		[Client] and I respect each other.

participated in an average of 6.8 sessions lasting between 40 and 60 minutes each (average 50.3 minutes).

Potential participants were recruited from a research registry, printed material advertising the study, and word-of-mouth. To be included in the study, participants had to be adults aged 18–65, meet DSM-V criteria for a major depressive disorder, currently experience at least moderate depressive symptoms (as measured by a Hamilton Rating Scale for Depression score ≥ 14; [79]), and be willing and able to provide informed consent. Individuals with a comorbid psychotic disorder, active suicidal or homicidal ideation, chronic depression, or current substance or alcohol abuse were excluded from the study. If an individual was suspected of experiencing psychosis or active suicidal ideation with intent or plan to harm themselves, the investigator terminated the screening interview and ensured that the individual obtained appropriate care, including but not limited to a referral to the psychiatric emergency room.

Included clients ranged from 22 to 65 years of age; 77% identified as female, and 62% identified as white. Clients were randomly assigned to an eight-session course of one of two psychotherapy conditions: cognitive behavioral therapy (CBT; 21 clients, 6 therapists) or inter-

personal psychotherapy (IPT; 18 clients, 5 therapists).[1]

Ratings of Working Alliance

Following the conclusion of each therapy session, both therapist and client participants completed the therapist and client versions of the revised short-form Working Alliance Inventory (WAI; [84]), a widely used measure of alliance in therapy. The WAI consists of three subscales capturing three aspects of working alliance:

- the *goal* subscale, which assesses the individual's belief that participants agree on the overall objectives of the treatment;
- the *task* subscale, which assesses the individual's belief that participants agree on the steps required to reach the goals mentioned above; and
- the *bond* subscale, which assesses the individual's respect and trust for the other participant in an emotional sense.

Each subscale consists of a set of statements which the individual rates on a five-point Likert-type scale ranging from 'seldom true' to 'always true'. Representative items for each subscale are presented in Table 4.1, and the distribution of scores observed in our dataset is illustrated in Figure 4.1.

Head Gesture Annotation

Head motion for each participant was automatically measured using the OpenFace facial behavior analysis toolkit [16]. Gestures of interest in the present study were limited to head nods (vertical motion along the pitch dimension) and head shakes (horizontal motion along the yaw dimension). A low-resource algorithm was selected to classify head gestures based on prior work using basic dimensions of motion [101, 105, 208]. Although these works derived head motion

[1]There were no statistically significant differences in working alliance ratings observed between the two treatment conditions.

$$\text{WAI} \sim 1 + \text{feature}_{\text{avg}} + \underbrace{(\text{feature}_{\text{dev}})}_{\text{session-level component}} + \underbrace{(1 + \text{feature}_{\text{dev}} \mid \text{therapist})}_{\text{therapist-level component}} + \underbrace{(1 + \text{feature}_{\text{dev}} \mid \text{therapist} : \text{client})}_{\text{client-level component}}$$

FIGURE 4.2
Inferential model specification in formula notation.

from the motion of a particular facial landmark between the eyes, our implementation instead incorporates head motion derived from the head tracking features provided by OpenFace [215]. Total distance traveled along each dimension was calculated over a rolling window of one second, and gestures were detected based on the top quartile of distance traveled within one second.

Speaking Turn Annotation

We define a 'speaking turn' as a contiguous speech segment from a single speaker until a non-speaking pause longer than one second. To determine speaking turns throughout the session, we performed speaker diarization (i.e., identifying when each speaker is actively speaking) using a voice activity detection algorithm available through openSMILE [55]. By applying this detection algorithm to each of the two participant microphones (client and therapist), the resulting annotations indicate whether the client or the therapist is presently speaking or, occasionally, if both are speaking.

4.4 Analysis

The present analysis consists of three stages. We begin with a set of inferential models to identify meaningful relationships between participant behaviors and working alliance ratings. We then incorporate these behaviors into a set of predictive models to estimate working alliance ratings.

TABLE 4.2
Summary statistics for features derived from head gestures and turn-taking behaviors.

	Client Behavior		Therapist Behavior	
	Mean	SD	Mean	SD
Head Nods (#)	208.25	47.75	208.89	50.04
Head Shakes (#)	162.07	71.58	167.51	52.17
Turn Length (s)	2.817	1.007	3.333	3.173
Wait Time (s)	1.305	1.899	1.854	1.483
Listening Nods (%)	0.229	0.070	0.236	0.078
Listening Shakes (%)	0.184	0.081	0.221	0.065

Finally, we perform a set of ablation studies to examine the value of including specific categories of behavior features: (1) client behavior vs. therapist behavior, and (2) head gestures vs. turn-taking behaviors.

Our feature set is primarily composed of the two sets of features derived from head gestures and speaking turns, as described in Section 4.3. Four additional features were derived from head gestures and turn-taking behaviors to identify head gestures while listening. We define therapist 'listening nods' as the percentage of client turns during which the therapist nods their head; a similar feature for client 'listening nods' is also computed for the client. We also define two 'listening shakes' features in the same manner for the head shake gestures of either client or therapist while listening. Our complete feature set, computed at the session level, consists of six features: head nods, head shakes, speaking turn length, wait time (pause length between the end of the partner's turn and the start of the speaker's), listening nods, and listening shakes. Summary statistics for all features are presented in Table 4.2.

Inferential Analysis

Due to the nested structure of our recorded client-therapist interactions, we utilize a multilevel modeling approach to account for multiple sessions per client and multiple clients per therapist.

TABLE 4.3

Client Ratings — Population-level effects from inferential models of working alliance ratings.

		Client Behavior			Therapist Behavior		
		Median	89% HDI	Sig.	Median	89% HDI	Sig.
OVERALL SCALE	Head Nods (#)	5.93	[0.00, 9.06]	⋆	−2.42	[−7.89, −0.15]	
	Head Shakes (#)	−6.89	[−6.02, −2.43]	⋆⋆	−2.20	[−6.89, 2.58]	
	Turn Length (s)	−0.14	[−0.48, 0.17]		−0.05	[−0.27, 0.17]	
	Wait Time (s)	−0.01	[−0.11, 0.10]		−0.01	[−0.12, 0.09]	
	Listening Nods (%)	4.29	[1.57, 7.11]	⋆⋆	−1.66	[−5.18, 1.68]	
	Listening Shakes (%)	−4.17	[−6.05, −2.15]	⋆⋆	−3.16	[−6.70, 0.48]	
GOAL SUBSCALE	Head Nods (#)	3.27	[−1.83, 6.24]		−4.18	[−9.79, −0.08]	⋆
	Head Shakes (#)	−6.58	[−6.35, −0.26]	⋆⋆	−1.25	[−7.99, 3.22]	
	Turn Length (s)	−0.18	[−0.53, 0.17]		−0.11	[−0.34, 0.12]	
	Wait Time (s)	0.01	[−0.11, 0.12]		−0.01	[−0.12, 0.10]	
	Listening Nods (%)	3.62	[0.52, 6.71]	⋆	−2.67	[−6.45, 0.98]	
	Listening Shakes (%)	−4.37	[−6.43, −2.21]	⋆⋆	−3.42	[−7.25, 0.48]	
TASK SUBSCALE	Head Nods (#)	4.54	[−0.31, 10.47]		−5.32	[−9.24, 0.10]	⋆
	Head Shakes (#)	−7.27	[−10.22, −3.16]	⋆⋆	−2.48	[−7.88, 0.28]	
	Turn Length (s)	−0.12	[−0.48, 0.25]		−0.02	[−0.27, 0.23]	
	Wait Time (s)	−0.03	[−0.15, 0.10]		−0.04	[−0.16, 0.08]	
	Listening Nods (%)	5.51	[2.34, 8.48]	⋆⋆	−1.27	[−5.04, 2.58]	
	Listening Shakes (%)	−4.67	[−6.91, −2.40]	⋆⋆	−3.83	[−7.82, 0.31]	
BOND SUBSCALE	Head Nods (#)	4.45	[−0.83, 7.83]	⋆	−1.84	[−4.54, 4.27]	
	Head Shakes (#)	−4.71	[−6.51, 0.24]	⋆	−1.89	[−7.01, 6.01]	
	Turn Length (s)	−0.18	[−0.52, 0.15]		−0.04	[−0.27, 0.19]	
	Wait Time (s)	−0.01	[−0.12, 0.11]		0.01	[−0.09, 0.12]	
	Listening Nods (%)	3.57	[0.41, 6.60]	⋆	−0.87	[−4.28, 2.53]	
	Listening Shakes (%)	−3.07	[−5.36, −0.77]	⋆	−2.70	[−6.37, 1.12]	

HDI = highest density interval, Sig. = significance, ⋆ $pd > 95\%$, ⋆⋆ $pd > 99\%$.

TABLE 4.4

Therapist Ratings — Population-level effects from inferential models of working alliance ratings.

		Client Behavior				Therapist Behavior			
		Median	89% HDI		Sig.	Median	89% HDI		Sig.
OVERALL SCALE	Head Nods (#)	−1.04	[−2.72,	1.73]		0.85	[0.87,	4.18]	
	Head Shakes (#)	−2.33	[−4.79,	−0.79]		−1.25	[−3.20,	0.10]	⋆⋆
	Turn Length (s)	0.07	[−0.03,	0.17]		−0.07	[−0.24,	0.11]	
	Wait Time (s)	−0.02	[−0.07,	0.03]		−0.02	[−0.07,	0.03]	
	Listening Nods (%)	−0.82	[−2.51,	0.84]		2.13	[0.87,	3.36]	⋆⋆
	Listening Shakes (%)	−1.36	[−3.13,	0.43]		−0.87	[−1.93,	0.17]	
GOAL SUBSCALE	Head Nods (#)	0.76	[−3.76,	3.30]		1.94	[0.10,	4.54]	⋆
	Head Shakes (#)	−0.21	[−4.02,	0.15]		0.70	[−2.35,	−0.99]	
	Turn Length (s)	0.14	[0.02,	0.26]	⋆	0.01	[−0.20,	0.24]	
	Wait Time (s)	−0.06	[−0.12,	0.01]		−0.06	[−0.12,	0.01]	
	Listening Nods (%)	−0.33	[−2.41,	1.82]		2.67	[1.11,	4.18]	⋆⋆
	Listening Shakes (%)	−0.93	[−3.17,	1.30]		−0.54	[−1.87,	0.80]	
TASK SUBSCALE	Head Nods (#)	−1.39	[−2.60,	1.03]		1.76	[0.30,	4.53]	
	Head Shakes (#)	−4.14	[−6.64,	−1.10]	⋆	−3.73	[−3.51,	−1.02]	⋆⋆
	Turn Length (s)	0.15	[0.03,	0.27]	⋆	−0.01	[−0.24,	0.21]	
	Wait Time (s)	−0.05	[−0.12,	0.01]		−0.06	[−0.12,	0.01]	
	Listening Nods (%)	0.02	[−2.17,	2.21]		2.97	[1.36,	4.54]	⋆⋆
	Listening Shakes (%)	−1.17	[−3.47,	1.22]		−0.96	[−2.36,	0.37]	
BOND SUBSCALE	Head Nods (#)	−2.15	[−3.05,	1.10]		0.27	[−0.95,	2.78]	
	Head Shakes (#)	−1.08	[−4.32,	0.99]		−0.72	[−1.83,	−1.73]	⋆⋆
	Turn Length (s)	−0.07	[−0.15,	0.02]		−0.21	[−0.35,	−0.07]	⋆⋆
	Wait Time (s)	0.04	[0.01,	0.08]	⋆	0.05	[0.01,	0.09]	⋆
	Listening Nods (%)	−2.24	[−3.43,	−1.06]	⋆⋆	0.81	[−0.37,	1.93]	
	Listening Shakes (%)	−1.92	[−3.38,	−0.52]	⋆	−1.16	[−1.94,	−0.36]	⋆

HDI = highest density interval, Sig. = significance, ⋆ $pd > 95\%$, ⋆⋆ $pd > 99\%$.

Recognizing the multilevel structure of such interactions is critical, as these observations are not wholly independent, and such dependencies could bias parameter estimation or model building during training time [47]. We follow an established method for decomposing longitudinal data into three separate components [77].

- The *session-level* components capture how each session attended by a particular client compares to the other sessions attended by that client. Features at this level are those described in the previous section.
- The *client-level* components capture how each client compares to the other clients interacting with the same therapist. Features at this level aggregate all sessions attended by the same client.
- The *therapist-level* components capture whether each therapist's sessions tend to have higher or lower measures than the other therapists' sessions. Features at this level aggregate all sessions conducted by a given therapist, including all of their clients.

We approach our models from a Bayesian perspective. Bayesian methods provide a means of augmenting pre-existing domain knowledge (in the form of a prior distribution) with data-driven updates (in the form of observed data) to construct more robust models than either technique can achieve individually [64]. These analyses were performed using the `bambi` Python package [37], a high-level interface for the probabilistic programming framework PyMC3 [176]. Models were estimated through Markov chain Monte Carlo [146] via the No-U-Turn Sampler algorithm [89]. The model specification is presented in Figure 4.2. This equation describes the form of the model, in which each term includes an implied coefficient: these coefficients are parameters estimated during training time.

Interpretation of these models requires examining the resulting posterior distribution (the estimated distribution after observed-data updates) for each model parameter. To quantify these posterior distributions, we measure the posterior median and the 89% highest density interval (HDI). These two measures help us study the central tendency and spread, respectively, for each

of the model parameters (also known as *effects*). The posterior median minimizes absolute error; the 89% HDI is common in Bayesian analysis, as it is more stable than the 95% HDI [123]. To understand the significance of the observed results, we also calculate the probability of direction (pd), a metric ranging between 50% and 100%, indicating the probability that a given parameter has the same sign as the posterior median [133]. We interpret pd values greater than 95% as 'significant' and pd values greater than 99% as 'highly significant'. Table 4.3 and Table 4.4 present the results obtained from the inferential analyses of client and therapist working alliance ratings, respectively. Note that each row of the table indicates a separate model, and that client behavior models were examined independently of therapist behavior models.

We observe that head gestures when listening are some of the client's most significant predictors of higher working alliance ratings. On the other hand, therapist behaviors had fewer significant associations with therapist ratings: the turn-taking features (turn length and wait time) were more strongly associated with working alliance ratings from the therapist. In both cases, the working alliance ratings were more associated with the behavior of the person providing the ratings than with the behavior of their partner.

Predictive Models

To evaluate the predictive power of head gestures and turn-taking behaviors in estimating working alliance ratings, we developed a set of models targeting each WAI subscale. Using the therapist-level, client-level, and session-level aggregated features (see Section 4.4 for details), we evaluated three predictive modeling procedures: support vector regression (SVR; [50]), Elastic Net [216], and random forests [26]. These algorithms were selected based on their ability to perform well on small datasets.

Model hyperparameters were automatically selected using a nested leave-one-therapist-out cross-validation approach to minimize train-test data contamination. For each therapist ($n = 11$), all sessions conducted by that therapist were designated as the test set, while all other sessions

TABLE 4.5
Performance metrics of predictive models: Root Mean Square Error, median and standard deviation.

	Client Ratings			
	Overall	Goal	Task	Bond
Baseline	0.82 (0.21)	0.86 (0.21)	0.94 (0.24)	0.85 (0.22)
SVR	**0.63 (0.22)**	0.69 (0.22)	0.74 (0.19)	**0.60 (0.25)**
Elastic Net	0.65 (0.23)	**0.66 (0.22)**	**0.68 (0.23)**	0.65 (0.23)
Random Forest	0.72 (0.18)	0.73 (0.20)	0.73 (0.18)	0.77 (0.19)

	Therapist Ratings			
	Overall	Goal	Task	Bond
Baseline	0.39 (0.31)	0.61 (0.36)	0.61 (0.42)	0.36 (0.29)
SVR	**0.31 (0.27)**	0.42 (0.30)	**0.50 (0.36)**	**0.30 (0.23)**
Elastic Net	0.37 (0.25)	**0.42 (0.31)**	0.53 (0.35)	0.32 (0.23)
Random Forest	0.38 (0.21)	0.43 (0.26)	0.58 (0.28)	0.36 (0.29)

were designated as the training set. Within the training set, validation for each fold was performed similarly: the sessions from one therapist were used for validation, while the remaining sessions were used for training. Features were recomputed for each training run to ensure that they do not rely on values from the test set. Prediction performance during validation and testing was measured using the root mean squared error (RMSE) metric. A benefit of RMSE over other similar metrics (e.g., the coefficient of determination R^2) is its definition in the same units as the output variable — in this case, working alliance ratings — and its stability in smaller datasets. Table 4.5 compares the test-set performance for each prediction model. For comparison, we also include a baseline model predicting the mean from the training set. All three models performed above the baseline model: the SVR and Elastic Net models tended to achieve the lowest RMSE.

TABLE 4.6
Performance metrics of ablation studies: Root Mean Square Error, median and standard deviation.

	Client Ratings			
	Overall	Goal	Task	Bond
Client Behavior	**0.64 (0.25)**	**0.69 (0.23)**	**0.71 (0.26)**	**0.70 (0.28)**
Therapist Behavior	0.95 (0.29)	1.02 (0.30)	1.04 (0.28)	1.03 (0.30)
Gesture Features	0.70 (0.23)	0.75 (0.25)	0.76 (0.26)	0.78 (0.30)
Turn-Taking Features	0.71 (0.25)	0.77 (0.23)	0.78 (0.33)	**0.73 (0.29)**
Gest. + Turn. Features	**0.67 (0.27)**	**0.74 (0.26)**	**0.73 (0.27)**	0.74 (0.25)

	Therapist Ratings			
	Overall	Goal	Task	Bond
Client Behavior	0.64 (0.31)	0.80 (0.44)	0.84 (0.46)	0.64 (0.33)
Therapist Behavior	**0.44 (0.34)**	**0.55 (0.40)**	**0.71 (0.45)**	**0.38 (0.30)**
Gesture Features	0.51 (0.33)	0.61 (0.40)	0.63 (0.47)	0.47 (0.36)
Turn-Taking Features	0.53 (0.36)	0.64 (0.37)	0.65 (0.47)	**0.44 (0.30)**
Gest. + Turn. Features	**0.49 (0.34)**	**0.59 (0.38)**	**0.60 (0.42)**	0.45 (0.31)

Ablation Studies

Following evaluation of the predictive models, we wanted to understand better the predictive value of including specific categories of features. We formulated two ablation studies to investigate: (1) behavior features from the therapist alone versus features from the client alone, and (2) head gesture features versus turn-taking features. Therapist-only features included features derived only from the therapist's behavior, and likewise for the client. Head gesture features are derived from head gestures alone (nods, shakes), independent of turn-taking behaviors (turn length, wait time). For comparison, we also present a third condition (referred to as 'Gest. + Turn. Features' in Table 4.6): the inclusion of both gestures and turn-taking features, but without the listening nods and listening shakes features that are derived from their combination. Table 4.6 compares the predictive performance of each of these models for both ablation studies.

4.5 Discussion

The present analysis sought to assess the value of computational nonverbal behavior analysis in estimating working alliance strength between therapists and clients. In this work, we investigated this proposition in three aspects: (1) a series of inferential analyses to identify general trends in behavior, (2) predictive model training to assess the ability to estimate working alliance ratings, and (3) a set of ablation studies to examine the significance of particular feature subsets. From these results, we identified some overall trends of note.

Participant ratings of the working alliance are largely uninformed by the behavior of the other participant. A consistent theme throughout these results is the suggestion that client behaviors do not offer much insight into therapist ratings, and similarly that therapist behaviors do not offer much insight into client ratings. This result corroborates prior work suggesting a frequent disconnect between therapist and client perception of the alliance [165, 167]. Also of note is the trend that client behaviors appear to hold more predictive power toward client ratings than therapist behaviors hold toward therapist ratings. This result is a valuable finding, as previous work has established that client ratings of the working alliance are the most reliable indicators of positive therapy outcomes, compared to therapist and observer ratings [92].

Head gestures tend to be more reflective of the task-oriented components of the working alliance, while turn-taking behaviors tend to be more reflective of the relationship-oriented component. As in many similar multimodal analyses [157, 172], our results identify trends in the salience of particular behavioral signals during the prediction of different outcome measures (Table 4.6). We note that turn-taking behaviors (speaking turn length and wait time) were primarily associated with the relationship-oriented component of the working alliance ratings — the bond subscale. On the other hand, head gestures (head nods and head shakes) were associated mainly with the working alliance ratings' task-oriented components — the goal and task subscales. There are similarities between these connections and those identified in studies of rapport, which recognize head gestures as more 'contentful' interaction signals [73, 198] and

turn-taking patterns as more indicative of trust and respect [194]. We also note that the derived features (listening nods and listening shakes) were more predictive of the goal and task subscales than the bond subscale. This result could be attributed to prioritization among behavior signals, indicating that head gestures are a 'stronger' signal than turn-taking behaviors.

Beyond simply being *uninformed* by the partner's behavior, in certain cases, working alliance ratings are *misinformed* by the partner's behavior. A comparison of the behavior patterns associated with client ratings (Table 4.3) and therapist ratings (Table 4.4) reveals a few notable divergences. In one case, an increase in nodding on the part of the therapist was generally associated with the therapist providing *higher* ratings on the goal subscale. However, this same therapist behavior was associated with *lower* goal and task subscale ratings from the client. Similarly, when clients nodded more frequently when listening, clients tended to provide *higher* ratings on all subscales, but therapists tended to provide *lower* ratings. These results seem to be consistent with other research, which found that therapy participants often 'misread' the behavioral cues of their partner [86, 165]. Despite this, our computational models were capable of predicting both participants' self-reported ratings of working alliance with moderate accuracy (Table 4.5).

4.6 Conclusion

The *working alliance* is a critical piece of the interaction between client and therapist that captures the collaborative aspect of the therapeutic relationship. A strong working alliance has been associated with several measures of positive therapy outcomes, but is often difficult to identify, as its definition relies on the subjective perspectives of both the client and the therapist. Further complexity is introduced by participant unawareness and misunderstanding of partner behaviors during the interaction.

Together, these results provide important insights into the challenges facing assessment of the working alliance during therapy and how computational behavior analysis holds promise for ad-

dressing these obstacles. Further research might explore the role of personal characteristics (e.g., personality, sociodemographic) or the client's psychiatric concerns (e.g., anxiety, depression), as the influence of these factors on nonverbal behavior is well-established [44, 148]. Although the sample of participants in this work is diverse and representative of the population in one community, generalizations to broader populations dissimilar to this one will require additional data collection and repeat analysis. A natural progression of this work would also include other behavioral signals, such as facial expressions or acoustic patterns in speech. The understanding gained through this line of research can foster the development of systems providing early detection of a weak working alliance, allowing for preemptive intervention and reduction in the barriers facing clients seeking treatment.

Acknowledgments

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Chapter 5

Linguistic Entrainment

As discussed in prior chapters, a strong working alliance has been extensively linked to many positive therapeutic outcomes. We can learn much about the strength of this alliance through participants' behavior, even at the fundamental level of facilitative behavior, but we now narrow our focus to convergent behavior. Although many aspects of therapy sessions are worth thorough examination, language use is of particular interest given its recognized relationship to similar dyadic concepts such as rapport, cooperation, and affiliation. Specifically, in this chapter we study language entrainment, which measures how much the therapist and client adapt toward each other's use of language over time. We explore these questions through the use of structural equation modeling (SEM) techniques, which allow for both multilevel and temporal modeling of the relationship between the quality of the therapist-client working alliance and the participants' language entrainment.

The work described in this chapter first appeared in the following publication:

> Alexandria K. Vail, Jeffrey Girard, Lauren M. Bylsma, Jeffrey F. Cohn, Jay Fournier, Holly Swartz, Louis-Philippe Morency. Toward Causal Understanding of Therapist-Client Relationships: A Study of Language Modality and Social Entrainment. *Proceedings of the Twenty-Fourth International Conference on Multimodal Interaction (ICMI 2022)*, Bangalore, India, 2022.
>
> https://doi.org/10.1145/3536221.3556616

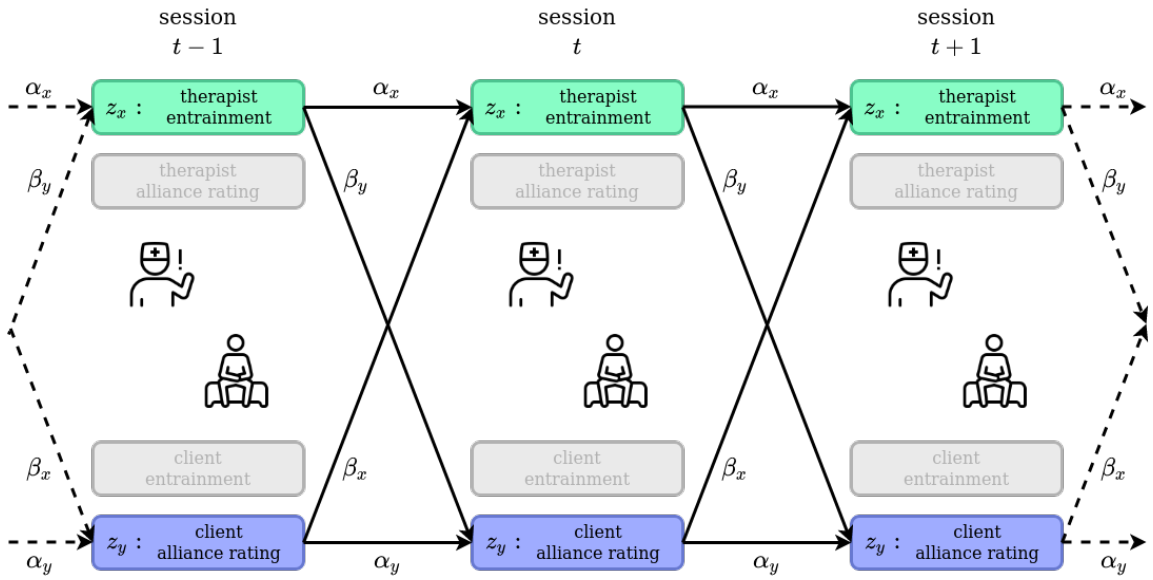


FIGURE 5.1
Example illustration of the structure of the therapist-entrainment/client-alliance analysis. During each session, we calculated an entrainment score (style and content) based on each participant's behavior, and after each session, each participant provided a rating of the working alliance (goal, task, and bond subscales). Edge labels (α_x, α_y, β_x, β_y) and node labels (z_x, z_y) correspond to the parameters introduced in Section 5.5 and Figure 5.2. A similar structure was mirrored for the therapist-entrainment/therapist-alliance, client-entrainment/client-alliance, and client-entrainment/therapist-alliance analyses.

5.1 Overview

Evidence suggests that the quality of the relationship between a client and their therapist is one of the most critical factors in determining treatment success [92, 135]. Concretely, much of the current psychological literature on the client-therapist relationship focuses on what is known as the *working alliance* [91]. This concept aims to capture the *collaborative* aspect of the therapist-client relationship. The working alliance is generally considered consisting of three components: agreement on the overall goal of the treatment, agreement on the tasks required to reach that goal, and the feeling of emotional bond between the participants. A positive working alliance between client and therapist plays a crucial role in fostering numerous positive therapeutic outcomes, including reduction of the client's symptoms and concerns [62, 91, 92], reduced drug abuse and recidivism [132] and improved medication compliance [59]. Of particular note is the recognized relationship between the quality of the working alliance and client dropout [59, 118, 178].

Proactive detection of a poor working alliance is especially valuable in this case: by the time a client has decided to quit therapy, the time for potential intervention has already passed. Understanding the complexity of the therapist-client relationship is crucial for informed treatment decision-making.

While working alliance and therapist-client relationships are decidedly multimodal concepts, the modality of language use is of particular interest given its importance in understanding similar forms of dyadic interaction [35, 97, 98, 159]. Relatively few studies have examined approaches for evaluating the working alliance beyond explicit questionnaires. More importantly, no previous work has studied the causal direction of the relationship between language and working alliance. Studying this relationship through the lens of causality allows us to go beyond correlation and address a broader range of research questions, such as the ones we focus on in this chapter: does language behavior affect how the working alliance is perceived, or does working alliance perception affect how language is used?

This chapter builds upon structural equation modeling (SEM) techniques to investigate the causal relationship between language use and working alliance. In particular, we introduce a specific method of structuring this model that allows us to study both relationships over time (temporal modeling) and patterns within individuals (multilevel modeling). Given the highly social nature of therapy sessions, we focus on *entrainment* in participant language. Linguistic entrainment is the process of multiple interlocutors (in our case, a client and their therapist) converging toward each other's use of language. We study linguistic entrainment in terms of both stylistic properties and content properties.

The structure of this chapter consists of eight sections. In the next section, we review previous literature on behavior detection, working alliance, and linguistic entrainment (Section 5.2), and the following section provides a brief overview of the dataset used in this analysis (Section 5.3). Section 5.4 describes the definition and computation of our features and labels. We then devote Section 5.5 to an in-depth explanation of the SEM-based model we use in our anal-

ysis. The primary contributions of the chapter lie in the next two sections: Section 5.6 evaluates the performance of this model in relation to other commonly used modeling techniques, while Section 5.7 interprets the model's conclusions and discusses the implications of these results for behavioral research. The final section summarizes the main findings of this work and identifies areas for further research.

5.2 Related Work

Interpersonal coordination is a behavioral phenomenon where multiple interacting individuals adapt their behavior together over time [199], which can take many forms [30]. Previous research has demonstrated that humans will coordinate their movements [3], voices [96, 163], and other communicative behaviors [131] to match each other during an interaction. A considerable amount of work has been published on the relationship between prosocial outcomes and behavioral coordination: increased interpersonal coordination during interaction leads to improved cooperation and collaboration [209], as well as higher self-reported ratings of rapport [166] and affiliation [95].

Despite this growing body of literature, relatively little work has focused on the role of interpersonal coordination in psychotherapy (cf. [1, 2, 160, 210]). Within this area of research, most prior work on therapy sessions has focused primarily on movement synchrony [119, 164]. In this analysis, we draw from related literature in social psychology that examines the role of *language entrainment* as a predictor of prosocial outcomes. Significant evidence exists to suggest that increased language style matching, in particular, leads to higher ratings of social intimacy, stability, and involvement [97, 98]. Language entrainment has also been linked to increased perception of support [159] and the general positivity of the interaction in question [35]. In long-term social relationships, language entrainment has also been shown to predict child attachment security significantly in parental relationships [24]. Inspired by this adjacent literature, this analysis explores whether language entrainment can also serve as a reliable and objective indicator of the quality

of the therapeutic working alliance.

5.3 Dataset

The data used in this chapter originate from the same audiovisual recordings described in Chapter 4. These recordings were collected from 266 therapy sessions between 39 unique clients and 11 unique therapists. Each therapist met with an average of 3.6 unique clients, and each client participated in an average of 6.8 sessions lasting between 40 and 60 minutes each (average 50.3 minutes).

Potential participants were recruited from a research registry, printed material advertising the study, and word-of-mouth. To be included in the study, participants had to be adults aged 18–65, meet DSM-5 criteria for a major depressive disorder[1], currently experience at least moderate depressive symptoms (as measured by a Hamilton Rating Scale for Depression score ≥ 14; [79]), and be willing and able to provide informed consent. Individuals with a comorbid psychotic disorder, active suicidal or homicidal ideation, chronic depression, or current substance or alcohol abuse were excluded from the study. If an individual was suspected of experiencing psychosis or active suicidal ideation with intent or plan to harm themselves, the investigator terminated the screening interview and ensured that the individual obtained appropriate care, including but not limited to a referral to the psychiatric emergency room.

Included clients ranged from 22 to 65 years of age; 77% identified as female, and 62% identified as White. Clients were randomly assigned to an eight-session brief course of one of two empirically supported psychotherapy conditions: cognitive behavioral therapy (CBT; 21 clients, 6 therapists) or interpersonal psychotherapy (IPT; 18 clients, 5 therapists).[2]

[1]The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5; [6]) is a taxonomy of psychiatric disorders published by the American Psychiatric Association. This manual serves as the primary diagnostic tool for psychiatric diagnosis and treatment in the United States.

[2]There were no statistically significant differences in working alliance ratings observed between the two treatment conditions.

TABLE 5.1
Sample items from both therapist and client versions of the Working Alliance Inventory.

Goal Subscale	Task Subscale	Bond Subscale
[Therapist] and I collaborate on setting goals for my therapy.	What I am doing in therapy gives me new ways of looking at my problem.	I believe [Therapist] likes me.
[Therapist] and I have established a good understanding of the kind of changes that would be good for me.	[Therapist] and I agree on what is important for me to work on.	I feel that [Therapist] appreciates me.
We are working towards mutually agreed upon goals.	[Client] and I agree about the steps to be taken to improve his/her situation.	I feel [Therapist] cares about me even when I do things that he/she does not approve of.
[Client] and I have a common perception of his/her goals.	[Client] and I both feel confident about the usefulness of our current activity in therapy.	I appreciate [Client] as a person.
		[Client] and I respect each other.

5.4 Language Entrainment and Working Alliance

Ratings of Working Alliance

Following the conclusion of each therapy session, both therapist and client participants completed the therapist and client versions of the revised short-form Working Alliance Inventory (WAI; [84]), a widely used measure of alliance in therapy. The WAI consists of three subscales capturing three aspects of a working alliance:

- the *goal* subscale, which assesses the individual's belief that participants agree on the overall objectives of the treatment;
- the *task* subscale, which assesses the individual's belief that participants agree on the steps required to reach the goals mentioned above; and
- the *bond* subscale, which assesses the individual's respect and trust for the other participant in an emotional sense.

Each subscale consists of statements that the individual rates on a five-point Likert-type scale ranging from 'seldom true' to 'always true'; the inventory contains 12 items for the client and 10

items for the therapist. Representative items for each subscale are presented in Table 5.1.

Language Style and Content Metrics

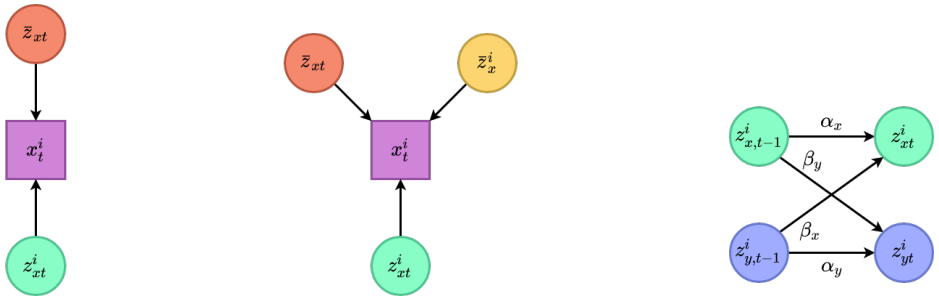
Language entrainment is the process of multiple interlocutors adapting toward each other's use of language throughout an interaction. Although there exist many operational definitions to measure this construct, we leverage and expand upon a metric called *reciprocal linguistic style matching* (rLSM; [144]). The original definition of rLSM utilizes the Linguistic Inquiry and Word Count dictionary (LIWC; [154]), a well-validated and established lexicon that organizes approximately 6,400 English words into several semantically or functionally similar categories. In particular, we use LIWC "function word" categories: pronouns, articles, prepositions, auxiliary verbs, adverbs, conjunctions, and negations. Function words are useful to examine because they are independent of context, and their use is often less conscious. The benefit of rLSM over other metrics is the reciprocal component, which aims to measure how much the interlocutors change toward each other over time, rather than how much they may coincidentally speak with a similar style.

The rLSM score is initially calculated at the utterance level. Consider a therapist's response (T) to an utterance by the client (C): we aim to calculate the rLSM metric for the therapist's utterance. Since utterance T is a response to utterance C, we define rLSM_T as follows:

$$\text{rLSM}_T(S) = 1 - \frac{|S_C - S_T|}{S_C + S_T + 0.0001} \tag{5.1}$$

Here S represents any LIWC category score (e.g., negations) computed for client and therapist utterances (S_C and S_T, respectively). The total rLSM score for a statement is the average score of all function word categories. This score is calculated for each utterance during the session, and all utterance scores from each session are then averaged to determine each participant's session-level rLSM score.

We also propose an extension to rLSM, which studies the "content" component of language for contrast against the "style" component of language. We approximate this content component



(A) $x_t^i = \bar{z}_{xt} + z_{xt}^i$
The CLPM measurement component for x_t^i. A similar structure is mirrored for y_t^i.

(B) $x_t^i = \bar{z}_{xt} + \bar{z}_x^i + z_{xt}^i$
The RI-CLPM measurement component for x_t^i. A similar structure is mirrored for y_t^i.

(C) $z_{xt}^i = \boldsymbol{\alpha_x} z_{x,t-1}^i + \boldsymbol{\beta_x} z_{y,t-1}^i + e_{xt}^i$
The temporal deviation component common to both CLPM and RI-CLPM.

FIGURE 5.2
Breakdown of the essential components of the CLPM and RI-CLPM techniques for a given session t.

using the following LIWC categories: affective words; social words (family, friends); words relating to cognitive, perceptual, and biological processes (seeing, feeling; health); and words relating to motivation/drives and personal concerns (risk, reward; leisure, religion). We term this new metric rLCM — reciprocal linguistic content matching.

5.5 Causal Model Introduction

Our model was designed with several desired principles in mind. First, we needed our model to be *interpretable*. Although the nature of the present analysis is primarily exploratory, we begin with some degree of expert domain knowledge and initial hypotheses as to the underlying structure of the data. For example, we expect that some individuals will adapt their language more than others ([158]; requiring multilevel modeling) and that working alliance ratings tend to increase over time ([85]; requiring temporal modeling).

To leverage these existing theoretical foundations, we turn to structural equation modeling (SEM) techniques [51]. SEM is a set of multivariate techniques that are generally confirmatory in nature, aiming to test whether a particular model structure fits a given dataset [127]. Unlike traditional machine learning models, SEM primarily leverages not the raw data provided to it but the covariance matrix: the goal is to minimize the distance between the observed and model-implied

matrices. SEM also offers some advantages in our particular case. Given the additional overhead and sensitivity required to collect rich healthcare data, such as our own dataset introduced in Section 5.3, these healthcare datasets are often of a smaller size than those in other domains of multimodal research. In reducing the number of estimated variables by imposing a theoretical structure, SEM also allows us to explicitly account for the variance due to the inevitable measurement error present in psychological data. These features allow us to attain greater statistical power with fewer samples.

Given that we pursue the use of SEM for our analysis, we must design the underlying structure fundamental to these techniques. We intend to evaluate the relationship between the participants' perception of the working alliance and the adaptation of their language use toward their conversational partner, and in particular, the direction of this relationship: we are interested in *causality* in the data. Given the longitudinal nature of our dataset, the standard practice is to turn to the family of cross-lagged panel models (CLPMs; [34]). Finally, we must consider that our observations follow the same individuals over time, so we must also include consideration for participant-level patterns. We expect that participants will differ in their personal tendencies simply due to personality or other individual characteristics; for example, some people may be more inclined to adapt their language than others. This final consideration leads us to a modern hierarchical extension of the CLPM: random intercept cross-lagged panel modeling (RI-CLPM; [78]). The following subsections describe the intuitions and definitions of the classic CLPM as well as the improvements and benefits introduced by the RI-CLPM extension.

Cross-Lagged Panel Modeling

Cross-lagged panel models (CLPM; [34]) involve the evaluation of the effect of two (or more) variables on each other over time. Consider x and y as two distinct variables (e.g., entrainment score and working alliance rating) from participant i measured over multiple time points (sessions) t. We aim to evaluate the relationship between x and y. The first important intuition

behind CLPM techniques is the idea that a measured variable x (or y) is composed of a mean and a variation from that mean. This intuition can be formulated as follows (see Figure 5.2a for an illustrated breakdown):

$$x_t^i = \bar{z}_{xt} + z_{xt}^i; \qquad y_t^i = \bar{z}_{yt} + z_{yt}^i; \tag{5.2}$$

where z_{xt}^i and z_{yt}^i represent the participant's temporal deviations from the temporal group means $\bar{z}_{xt}$ and $\bar{z}_{yt}$, respectively.

The second important intuition behind this model is that these temporal deviations z_{xt}^i are affected not only by previous temporal instances of itself, but also previous temporal instances of the other variable, z_{yt}^i; the same concept applies symmetrically for temporal variations of the other measured variable. This intuition is where the "cross-lagged" term in this approach originates. We can formally model these temporal deviations on the latent variables z_{xt}^i and z_{yt}^i as follows (Figure 5.2c):

$$z_{xt}^i = \alpha_x z_{x,t-1}^i + \beta_x z_{y,t-1}^i + e_{xt}^i, \tag{5.3}$$

$$z_{yt}^i = \alpha_y z_{y,t-1}^i + \beta_y z_{x,t-1}^i + e_{yt}^i. \tag{5.4}$$

The parameters α_x and α_y are autoregressive parameters that account for the temporal stability of these constructs: that is, the closer these parameters are to one, the more stable the rank order of individuals across time points. The parameters e_{xt}^i and e_{yt}^i represent residuals. The cross-lagged parameters β_x and β_y are fundamental to this family of models — by comparing the crossed effects of x on y (and vice versa), we can identify evidence to suggest the causal predominance of one direction over the other.

Random Intercept Cross-Lagged Panel Modeling

Following Hamaker et al. [78], we use an extension of CLPM that allows each participant to have their own individual variation compared to the group-level means $\bar{z}_{xt}$ and $\bar{z}_{yt}$. This model is named the random intercept cross-lagged panel model (RI-CLPM). RI-CLPM is a multilevel model where observations are nested within individuals. This model includes a random intercept that allows it to account not only for temporal stability, but also trait-level stability. With this in mind, Equation 5.2 can be rewritten as follows (see Figure 5.2b for an illustrated breakdown):

$$x_t^i = \bar{z}_{xt} + \bar{z}_x^i + z_{xt}^i, \qquad y_t^i = \bar{z}_{yt} + \bar{z}_y^i + z_{yt}^i, \tag{5.5}$$

where the added parameters $\bar{z}_x^i$ and $\bar{z}_y^i$ represent the participant's individual trait-level deviations from the existing temporal group means. In this case, the parameters z_{xt}^i and z_{yt}^i now represent the participant's temporal deviations from their personalized expected scores (i.e., $\bar{z}_{xt} + \bar{z}_x^i$ and $\bar{z}_{yt} + \bar{z}_y^i$) rather than deviation from the temporal group mean (i.e., $\bar{z}_{xt}$ and $\bar{z}_{yt}$). We can now express these deviations as follows (Figure 5.2c):

$$z_{xt}^i = \alpha_x z_{x,t-1}^i + \beta_x z_{y,t-1}^i + e_{xt}^i, \tag{5.6}$$

$$z_{yt}^i = \alpha_y z_{y,t-1}^i + \beta_y z_{x,t-1}^i + e_{yt}^i. \tag{5.7}$$

The autoregressive parameters α_x and α_y no longer represent merely the rank order of participants over time, but the degree of the within-person carry-over effect. For example, if this parameter is positive, it suggests that if a participant scored higher than their expected score at time point t, they are likely to also score higher than their expected score at time point $t + 1$.

One advantage of using the RI-CLPM over the CLPM is that it is effectively a generalization of the CLPM: if the additional elements are determined to be unnecessary, the additions tend toward zero and the model essentially 'collapses' to the base CLPM. Furthermore, in the case of the present analysis, we can reasonably assume that the effect the variables x and y have on

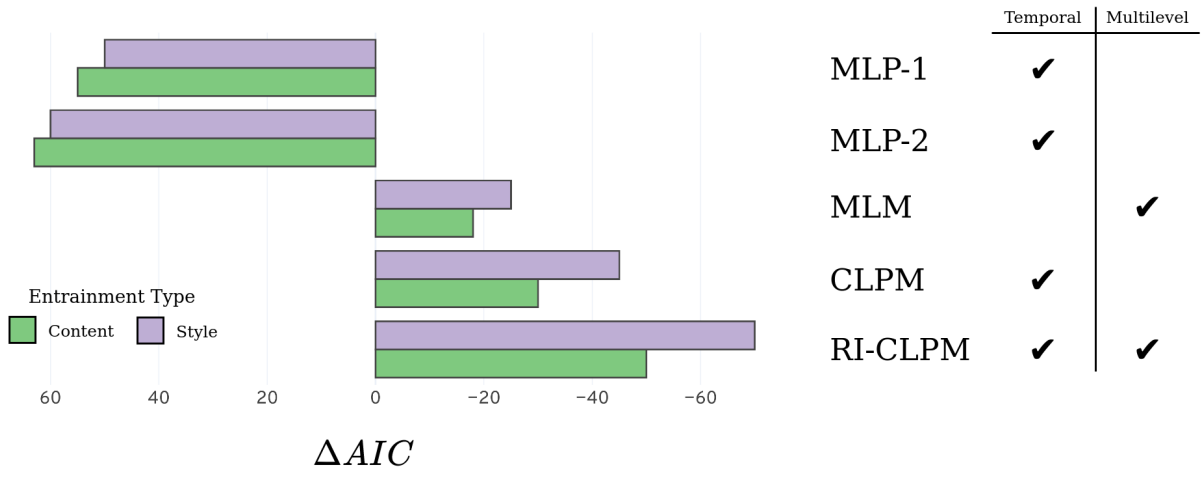


FIGURE 5.3
Comparative performance of baseline models relative to the linear model (LM). Note that AIC is a relative metric, and has no meaning in absolute terms: there are no "good" or "bad" AIC scores, only "better" or "worse" than another. Therefore, lower ΔAIC scores (further right in the chart) are better.

each other over time remains stable: our observed time points are roughly evenly spaced, and we do not perform any midpoint 'intervention' that would suggest that any particular interval differs from the other intervals. As a result, we tie parameters (i.e., α and β) across time points, providing us with many more degrees of freedom in our model and parameters that are more straightforward to interpret.

5.6 Prediction Experiment

Our first set of experiments compares RI-CLPM performance against other commonly used models, such as neural networks. As a reminder, an important goal when designing our model based on RI-CLPM was to leverage domain knowledge to reduce complexity and hopefully improve performance. Our model integrates inductive biases (domain knowledge) for both the temporal and the multilevel aspects of the data.

Baseline Models

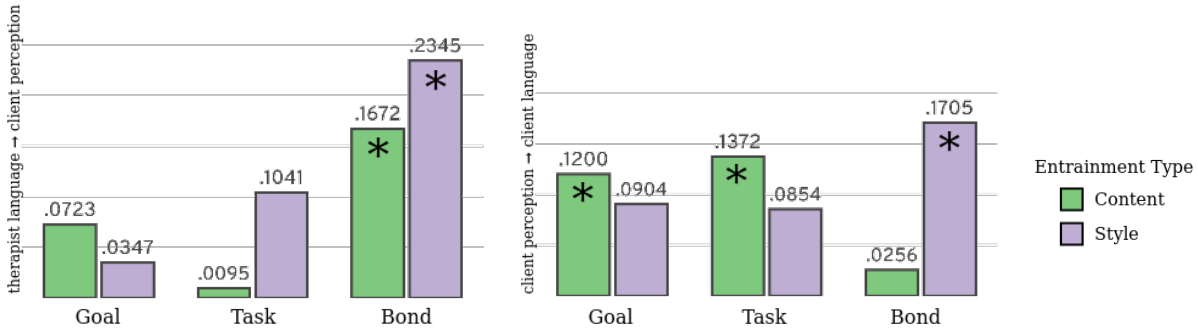
We compare our model with several commonly used machine learning models. We begin with neural networks: given the small number of data samples, we constrained ourselves to multi-layer perceptrons. We included two variants with one or two hidden layers (MLP-1 and MLP-2, respectively). To study the relative importance of the two inductive biases we included in our model, we included as baselines a multilevel linear model (MLM) and the standard CLPM. The comparison with the CLPM allows us to evaluate the importance of including the random intercept component. All models were compared in terms of the performance of a simple linear model (LM), which can also perform effectively with small datasets.

Prediction Metrics

One of the challenges when evaluating all of these models is selecting a metric that will be fair and comparable across models. Although many commonly used models (such as MLP models) are generally trained and evaluated in terms of their predictive performance (e.g., accuracy), SEM-based models have no directly corresponding notion of "prediction". Therefore, for this comparison, we rely on a metric revolving around *model fit*: Akaike's information criterion (AIC; [48]), which evaluates how well a given model's implied structure matches a given dataset. Rather than providing an "absolute" score, it instead offers evidence for the preference of one model over a set of others: in other words, there are no "good" or "bad" AIC scores, only scores that are "better" or "worse" than that of another model. This metric can be expressed as follows:

$$\text{AIC} = 2k - 2\ln(\hat{L}), \tag{5.8}$$

where k is the number of estimated parameters in the model and $\hat{L}$ is the maximum value of its likelihood function.



(A) Estimated cross-lagged parameters (β) evaluating the effect of the **therapist's entrainment** behavior on the **client's alliance** ratings. *How does the therapist's language affect the client's perception of the working alliance?*

(B) Estimated cross-lagged parameters (β) evaluating the effect of the **client's alliance** ratings on the **client's entrainment** behavior. *How does the client's perception of the working alliance affect their language?*

FIGURE 5.4
Highlighted results from the language analysis described in Section 5.7. Asterisks (*) indicate parameters statistically significantly different from zero ($p < 0.05$).

Results and Discussion

Figure 5.3 presents an overview of the performance of all models. Given that AIC is a relative metric, all scores are interpreted in terms of difference from the baseline model, the linear model. From this figure, it becomes apparent that the general pattern of better performance is achieved with the addition of temporal and multilevel elements — for such a relatively small but rich dataset, the importance of leveraging expert knowledge of both domain and dataset structure is evident.

5.7 Language Analysis

Our second set of experiments analyses the learned cross-lagged parameters (β_x and β_y) of the RI-CLPM model. Our goal is to study the relative effects of a participant's perception of the working alliance on their linguistic entrainment behavior. One benefit of our approach is the

ability to distinguish directional effects — that is, whether working alliance perception affects linguistic entrainment, or if linguistic entrainment affects working alliance perception.

Working alliance ratings were collected from both client and therapist at the end of each session: these working alliance ratings are divided into agreement on goals, agreement on tasks, and agreement on bond. We also calculated both a stylistic entrainment score and a content entrainment score for each participant during each session (see Section 5.4 for more details on the calculation of these metrics). We fit an RI-CLPM to each combination of language behavior and working alliance ratings. From these fitted models, we primarily examine the cross-lagged parameters that estimate the relationship between the two measured variables: see Section 5.5 for more details on the model.

Results

Highlighted results are presented in Figure 5.4. Numerous significant effects can be observed from these results. In general, the client's perception of the working alliance results in an increase in their style and content entrainment (Figure 5.4b). In particular, the client's perception of bond results in an increase in their stylistic entrainment, while their perception of the goal and task aspects of the working alliance result in an increase in their content entrainment.

From Figure 5.4a, we can see that the client's perception of bond is significantly influenced by both content and stylistic linguistic entrainment on the part of the therapist. On the other hand, the therapist's perception of the working alliance appears less impacted by linguistic entrainment: the only significant association observed is that an increase in the client's content matching results in an increase in the therapist's perception of task agreement ($\beta = 0.1179$).

Discussion

The present analysis was designed to determine the effect of language entrainment during therapy sessions on the participants' perception of the working alliance, and vice versa. The results

provide preliminary evidence to suggest a bidirectional but asymmetric relationship between these two constructs.

Stylistic entrainment is generally associated with perception of bond, while content matching is generally associated with perception of task and goal. By examining working alliance ratings at this granular level, we can observe that stylistic entrainment seems associated mainly with the perception of bond. In contrast, content matching appears primarily associated with the perception of task and goal.

Therapy clients express their perception of the working alliance through linguistic entrainment. Perhaps the most compelling finding to emerge from this analysis is the suggestion that the client appears to demonstrate their current perception of the working alliance through their linguistic entrainment behavior, as seen in Figure 5.4b.

Therapist linguistic entrainment has a notable impact on the client's perception of the working alliance bond. Finally, a third notable takeaway is that the therapist's language entrainment behavior seems to have a substantial impact on the client's perception of the working alliance, and particularly, their impression of the bond (Figure 5.4a).

These results, particularly those discussed in the latter two points, also demonstrate the importance of considering causality when investigating these relationships. A model that explores only correlation, as most commonly used models, would be unable to ascertain, for example, whether a client's linguistic entrainment affects their perception of the alliance or if their perception affects their entrainment.

5.8 Conclusion

The working alliance is a multifaceted concept that captures the collaborative aspect of the relationship between a therapist and their client. We use structural equation modeling (SEM) techniques to study the causal relationship between working alliance and language entrainment behaviors. We demonstrate that this kind of modeling can achieve excellent performance com-

pared to other standard machine learning models, with the added benefit of interpretability and causal analysis. Interpretation of the model reveals valuable insights into the dyadic interaction between therapist and client during therapy. In general, the language entrainment of the therapist can have an impact on the client's perception of the alliance, and the client's perception of the alliance is often reflected in their own language use.

Future work includes exploring the relationship between working alliance and other social behaviors, such as gestures, prosody, and facial expression; bringing these modalities together into a multimodal approach is also of great interest. Examining the relationship between these behaviors and the alliance throughout a single interaction at a more granular level may also reveal exciting relationships. Such findings could eventually be implemented in the form of a computer-mediated feedback system, aiding the therapist in recognizing the deterioration of the working alliance in the moment and allowing for more immediate intervention to address client concerns. Multimodal behavior analysis in therapy has many promising future paths: the ensuing enhancement of therapeutic interaction will help ensure that more people seeking therapy receive the treatment they need.

Acknowledgments

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Part III

Hybrid Modeling

"[T]he trick to being a scientist is to be open to using a wide variety of tools. The roots of statistics, as in science, lie in working with data and checking theory against data. I hope in this century our field will return to its roots. There are signs that this hope is not illusory."

– Leo Breiman, 2001 [26]

Chapter 6

Representation Learning

Characterizing the dynamics of behavior across multiple modalities and individuals is a vital component of computational behavior analysis. In machine learning, this process is referred to as *representation learning*. In this chapter, we present a novel approach to learning multimodal and interpersonal representations of behavior dynamics during one-on-one interaction. Our approach is enabled by the introduction of a multiview extension of latent change score models, which facilitates the concurrent capture of both inter-modal and interpersonal behavior dynamics and the identification of directional relationships between them. A core advantage of our approach is its integration of domain knowledge to model both multimodal and social aspects of client-therapist interaction. This allows our model to achieve strong predictive performance, despite the limited data set characteristic of this domain. Our results demonstrate improved performance over conventional approaches that rely upon summary statistics or correlational metrics. Furthermore, since our multiview approach includes the explicit modeling of uncertainty, it naturally lends itself to integration with probabilistic classifiers, such as Gaussian process models. We demonstrate that this integration leads to even further improved performance, all the while maintaining highly interpretable qualities.

The work described in this chapter first appeared in the following publication:

> Alexandria K. Vail, Jeffrey M. Girard, Lauren M. Bylsma, Jay Fournier, Holly A. Swartz, Jeffrey F. Cohn, Louis-Philippe Morency. Representation Learning for Interpersonal and Multimodal Behavior Dynamics: A Multiview Extension of Latent Change Score Models. *Proceedings of the Twenty-Fifth International Conference on Multimodal Interaction (ICMI 2024)*, Paris, France, 2023.
>
> https://doi.org/10.1145/3577190.3614118

6.1 Overview

To address mental health concerns successfully, it is critical to provide individuals with the necessary support to ensure their commitment to accomplishing their therapeutic treatment. One of the most important elements in fostering such commitment is the cultivation of a positive relationship between the client and the therapist. Empirical evidence has indicated that clients who share a positive relationship with their therapist are less likely to discontinue therapy [9] and more likely to experience favorable treatment outcomes [13, 122]. Therefore, it is essential to monitor the development of this relationship over the course of treatment to allow the therapist to adjust their approach to better meet the needs of the client. Unfortunately, obtaining genuine feedback from therapy clients can prove to be a challenge: clients often express hesitation due to concerns about confidentiality, fear of negative consequences, or a desire to please the therapist [125, 173]. However, computational modeling techniques have demonstrated considerable potential in simulating and forecasting other social constructs.

The task of modeling of human behavior is a challenging one, as it involves many factors. One such factor is the need to consider how each person affects and is affected by the other people around them [170, 202]. This reciprocity between interacting people is one of the greatest influences on an individual's behavior in such contexts [106]. Furthermore, modeling social behavior during therapeutic treatment can be even more challenging than modeling social behavior in other contexts. Clients often exhibit greater vulnerability, openness, and self-reflection during therapy than they do in their everyday behavior [65]. This heightened state of engagement can lead to more intense emotional experience and expression, which can significantly affect the nature of the therapeutic conversation [116].

Another factor complicating the study of human behavior is the fact that information is communicated through many different modalities simultaneously. It is well-established that verbal and nonverbal behavior is interconnected [10, 52, 136] and offer different kinds of information [29, 33], but during therapy, the relationship between the two is particularly significant. Re-

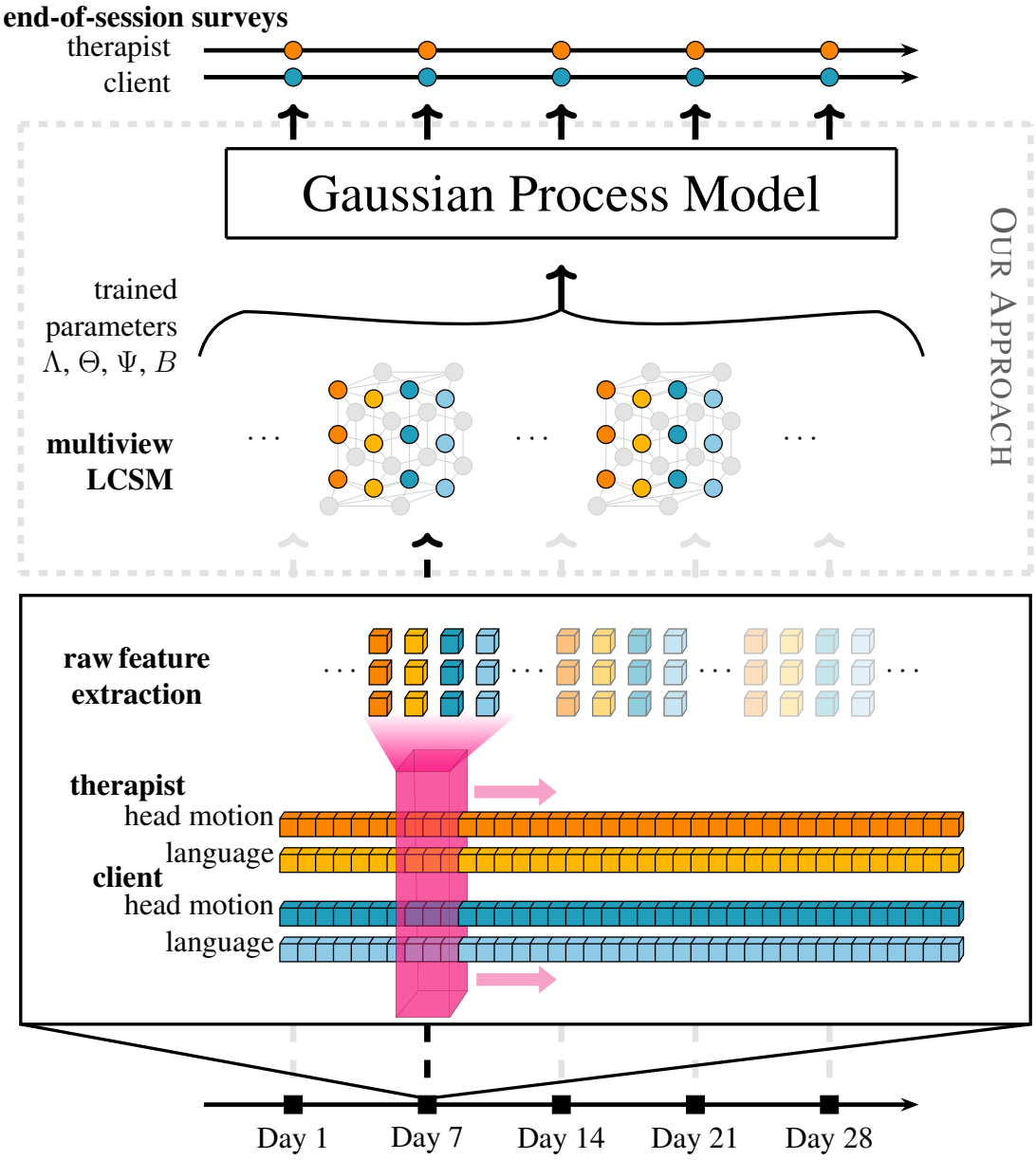


FIGURE 6.1
An overview illustration of the methodology presented in this work. We train one MVLCSM for each session by extracting behavior features from consecutive 45-second intervals. By extracting the learned parameters of this model, we obtain a representation that serves as input for our predictive models.

search has demonstrated that verbal behavior tends to more accurately reflect a person's thoughts, while nonverbal behavior tends to more accurately reflect a person's emotions [29, 151, 202]. However, this consistency (or inconsistency) of information provided across different modalities can reveal valuable insights into the client's therapeutic experience [10, 93, 147].

Finally, when studying human behavior, it is imperative to acknowledge that our behavior is not static, but rather changes over time. Examining the dynamics of behavior is critical, as it allows for the identification of patterns and trends, and potentially even recognition of causal relationships between variables [14, 185]. Observing how an individual adapts their behavior in response to changes in others' behavior can provide a wealth of information about the nature of their relationship [72, 115]. This observation is particularly valuable in the therapeutic context, where the client's reactions to different prompts or actions of the therapist also serve as valuable indicators of their current mental state [14, 135].

This chapter proposes a novel methodology for developing effective representations of human behavior during social interaction. Our suggested approach uses structural equation modeling to learn a representation of behavior dynamics that can offer explicit modeling of the relationships between behaviors and how each person's behavior affects and is affected by the behavior of others. An overview of the approach we introduce is illustrated in Figure 6.1. We then demonstrate an application of this approach in evaluating the strength of the relationship between a client and therapist during therapy sessions, which can be a particularly challenging context. This methodology has the potential to provide new and valuable perspectives into behavior patterns across individuals, modalities, and time.

6.2 Proposed Model

Our approach to modeling behavior dynamics involves a three-step process. First, we introduce our novel multiview extension of latent change score models, which allows for the simultaneous capture of multimodal and interpersonal dynamics. We then demonstrate how these models are

Goal Subscale	Task Subscale	Bond Subscale
[Therapist] and I collaborate on setting goals for my therapy.	What I am doing in therapy gives me new ways of looking at my problem.	I believe [Therapist] likes me.
[Therapist] and I have established a good understanding of the kind of changes that would be good for me.	[Therapist] and I agree on what is important for me to work on.	I feel that [Therapist] appreciates me.
We are working towards mutually agreed upon goals.	[Client] and I agree about the steps to be taken to improve his/her situation.	I feel [Therapist] cares about me even when I do things that he/she does not approve of.
[Client] and I have a common perception of his/her goals.	[Client] and I both feel confident about the usefulness of our current activity in therapy.	I appreciate [Client] as a person.
		[Client] and I respect each other.

TABLE 6.1
Sample items from both therapist and client versions of the Working Alliance Inventory.

used to learn rich representations of behavior. Finally, we employ these representations as input for a predictive model, enabling us to make accurate predictions for practical implementation.

Structural Equation Modeling

Structural equation modeling (SEM) is a multivariate statistical approach used to analyze complex relationships between latent and observed variables [51, 127]. Generally confirmatory in nature, SEM aims to test whether a hypothesized model fits a given dataset, involving the use of several mathematical *equations* describing a hypothesized *structure* of the data. This structure defines a set of relationships between latent and observed variables, such as factor loadings, causal pathways, and covariance matrices. If the model fits the data well, its structure provides us with insight into the underlying driving behavior patterns in the data, while also taking into account measurement errors and potentially confounding factors. In general, SEM has become increasingly popular for interdisciplinary research due to its ability to capture complexity within systems without sacrificing interpretability [156, 183, 213].

We selected this modeling technique over other traditional machine learning models for several reasons. The primary advantage we value is its ability to encode existing domain knowledge

and theory, allowing for the incorporation of meaningful and informed suggestions for the relationships between variables. SEM provides a graphical representation of the model that helps visualize complex relationships between factors. Furthermore, many popular black-box frameworks used in machine learning, such as deep neural networks, require large amounts of training data before producing meaningful results. In contrast, SEM can provide insight from smaller sample sizes with fewer observations since it combines data-driven parameter training with expert domain knowledge [114, 156]. This benefit is even more advantageous to our domain than most areas of multimodal research: the additional overhead and sensitivity required to collect rich multimodal behavior data, especially in healthcare, often leads to a smaller number of available observations than is available for other research areas.

SEM is commonly used for hypothesis testing by evaluating the fit of multiple models, each representing a different set of hypotheses about the structure of the data, in relation to the actual observed data. However, in contrast to this conventional use, in this work we use SEM as a representation of the underlying systems within our data. Although this use case allows us to capture the complexity of the relationships within the data in a novel and interesting way, it also requires careful model specification and parameter estimation. For this reason, we rely on established model specifications, validated in previous research, for our analysis [7, 196].

Latent Change Score Model

A well-defined structure is essential for accurate and reliable structural equation model-based analysis. In this study, we extend the structure of latent change score models, a family of models that are frequently used in psychological research for the study of longitudinal data [137]. In particular, we define a *multiview latent change score model* that allows us to simultaneously model patterns between modalities and individuals throughout an interaction.

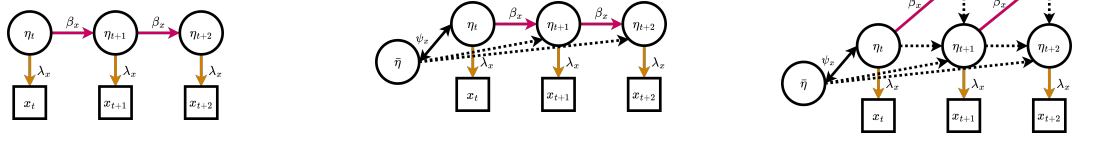
At the highest level, latent change score models are SEM structures that aim to estimate changes in a given variable over time. These models attempt to identify the underlying structure

of these changes through the use of both observed variables and latent factors. From a machine learning perspective, these models resemble an approach that takes advantage of supervised and unsupervised techniques to analyze longitudinal data. By incorporating domain knowledge about unobserved confounding factors (i.e., latent factors), these models help us better understand the relationship between variables.

The standard single-view latent change score model is illustrated in Figure 6.2c. Although the latent change score model can contain any number of measured time points (greater than two), the number of points to include is highly dependent on the available data [75, 137]. In our case, we have a few different elements to consider.

- We need our chosen duration of x_t to be a reliable measure of behavior during that time interval, e.g., to ensure that both individuals have sufficient time for speaking and listening behavior during each segment.
- Based on our duration of x_t, we need to ensure that the duration of each complete sequence (duration$(x_t) \times k$ points) allows a sufficient number of sample sequences to be drawn from the entire session to perform meaningful statistical modeling.
- We must ensure that we have enough time points per sequence to accurately estimate the free parameters in the model.

To achieve these objectives, it is crucial to select an appropriate duration and quantity of x_t

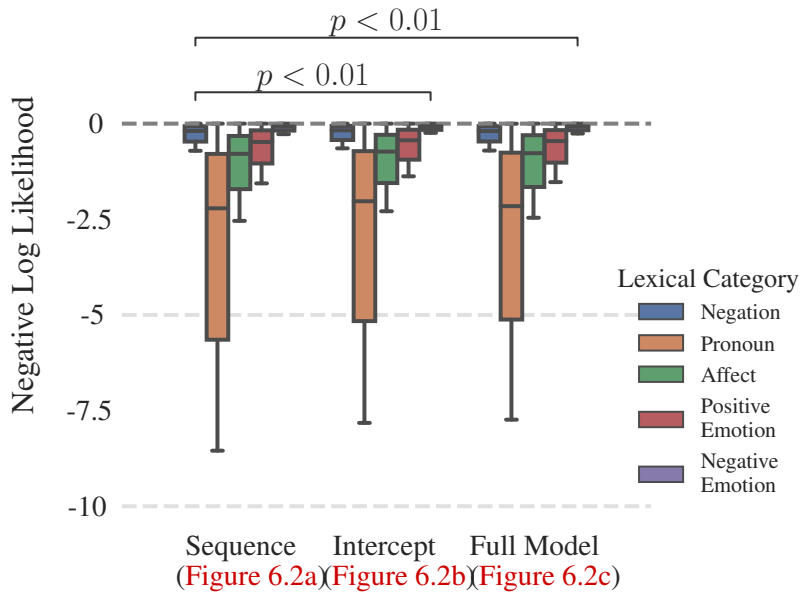


(A) Sequence-Only Model **(B)** Intercept-Added Model **(C)** Full Latent Change Score Model

FIGURE 6.2
Ablation steps to build the univariate latent change score model. Colored paths represent paths tied to each other (with the exception of black paths). Note that for clarity, self-variances are excluded from the illustration. Dotted lines indicate parameters constrained to the unit weight.

that balances the need for an accurate representation of individual behaviors with the need to maintain a suitable number of sample sequences and data points for robust statistical analysis. We selected a 45-second window for each time point x_t after evaluating the fit of the single view model on each of our behavior markers. Given this 45-second window, our average session duration of 50–60 minutes, and our models as specified earlier, we decided to proceed with a three-point sequence (see Section 6.3, Data Set). This decision results in having 60–80 input sequences per model, which is consistent with the typical suggestion of 10–20 sequences per free parameter [75]. Therefore, the single-view model upon which we expand our analysis consists of a sequence of three observed variables and five latent factors. We deconstruct this model into three ablation phases to define and later demonstrate the significance of each component. Figure 6.2 illustrates each step of this ablation and explains how they represent the theoretical framework behind the process of interest (in this case, client-therapist interaction).

Step 1: Latent sequence (Figure 6.2a). The core of this model is the representation of longitudinal data in its most primitive stage. The basic implementation of a three-part sequential SEM consists of the three measured variables (x_t, x_{t+1}, x_{t+2}) loaded onto their respective latent factors (η_t, η_{t+1}, η_{t+2}). These loadings (λ_x) represent the degree to which the latent construct explains the variance of the measured variable. This connection encodes the hypothesis that each measurement is the sum of the "true" latent value plus some amount of measurement error (self-variance, θ_x). We constrain these loadings to be equivalent for each time point because we expect that this relationship will not change over time, and doing so will improve the estimation and interpretability of the model. The three latent factors are connected with one-way causal paths, suggesting that the value at each time point is influenced by the value at the previous time point, along with the variance of the latent factor itself (ψ_{xt}). At this point, we can define our



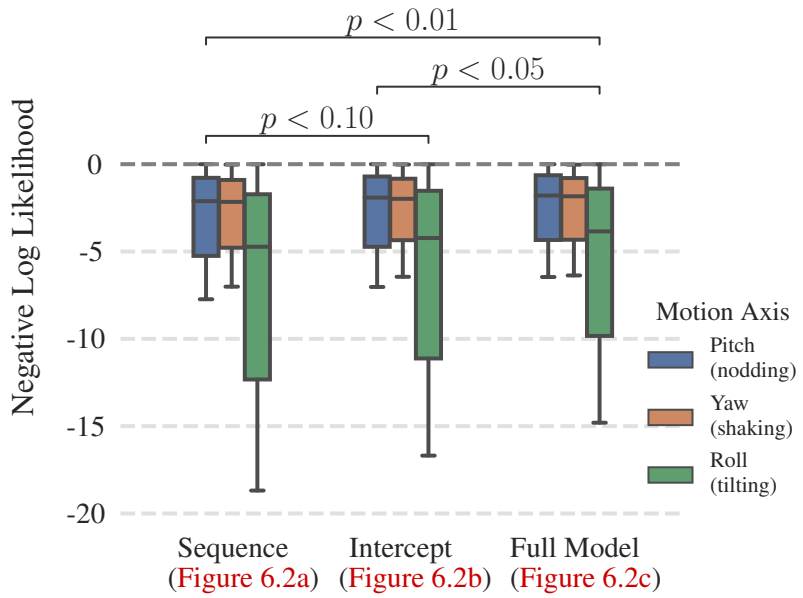


FIGURE 6.3
Average negative log-likelihood of converged univariate models across behavioral markers, with statistically significant differences annotated. Ablation across the sequence-only, added-intercept, and full variants of the latent change score model (LCSM; Figure 6.2) suggests that the inclusion of each additional structural element improves the fit of the model. Note that head motion-based models exhibit a significantly poorer fit in a univariate context compared to language-based models.

model using the following equations.

$$x_t = \lambda_x \eta_t + \theta_x \tag{6.1}$$

$$x_{t+1} = \lambda_x \eta_{t+1} + \theta_x \qquad \eta_{t+1} = \beta_x \eta_t + \psi_{xt} \tag{6.2}$$

$$x_{t+2} = \lambda_x \eta_{t+2} + \theta_x \qquad \eta_{t+2} = \beta_x \eta_{t+1} + \psi_{xt} \tag{6.3}$$

Step 2: Intercept (Figure 6.2b). The next component that we add to the model is the sequence *intercept* ($\bar{\eta}$). This intercept represents the value of a construct at the first time point, serving as a baseline against which future values of the construct are compared. Neglecting to include an intercept would represent the assumption that all sequences begin at the same value: an untenable premise. We can now define our latent factors with the following equations; note that the measured variables (x_t, x_{t+1}, x_{t+2}) will retain the same definition throughout.

$$\eta_t = \bar{\eta} + \psi_{xt} \tag{6.4}$$

$$\eta_{t+1} = \beta_x \eta_t + \bar{\eta} + \psi_{xt} \tag{6.5}$$

$$\eta_{t+2} = \beta_x \eta_{t+1} + \bar{\eta} + \psi_{xt} \tag{6.6}$$

Step 3: Latent change factors (Figure 6.2c). A defining element of the latent change score model is the inclusion of *latent change factors* ($\Delta\eta_{t+1}$, $\Delta\eta_{t+2}$). These second-order latent factors represent the change in the first-order latent factors over time. Inclusion of these factors helps the model account for variability in the dynamics across individuals — or, in our case, across different moments in the therapy session.

$$\eta_t = \bar{\eta} + \psi_{xt} \qquad \bar{\eta} = \psi_x \eta_t \tag{6.7}$$

$$\eta_{t+1} = \bar{\eta} + \eta_t + \Delta\eta_{t+1} + \psi_{xt} \qquad \Delta\eta_{t+1} = \beta_x \eta_t + \psi_{\Delta xt} \tag{6.8}$$

$$\eta_{t+2} = \bar{\eta} + \eta_{t+1} + \Delta\eta_{t+2} + \psi_{xt} \qquad \Delta\eta_{t+2} = \beta_x \eta_{t+1} + \psi_{\Delta xt} \tag{6.9}$$

Figure 6.3 illustrates the fit achieved by the univariate version of the model. In the case of this analysis, our objective is to simulate behavior dynamics between modalities and individuals during the interaction of a therapist and their client. Therefore, we extend the standard latent change score model by creating a multiview extension to incorporate multiple modalities and individuals in the analysis.

Multiview Extension

As a first step, we present the bivariate extension of the latent change score model, which enables the study of two forms of behavior dynamics over time. These data streams could originate from two modalities (multimodal dynamics) or from two people (social dynamics). For example, it could model the relationship between an increase in client nodding and an increase in therapist nodding; or, it could model the relationship between increased client head motion (nonverbal behavior) and their discussion of emotions (verbal behavior). Inclusion of covariance parameters across latent constructs, intercepts, and change factors of different behaviors allows us to consider these relationships when learning our SEM-derived data representations.

Before using our proposed model extension to learn representations to use in predictive models, we first evaluate how the inclusion of additional data streams (i.e., from univariate to bivariate) affects the model fit of the SEM. We performed two sets of experiments to evaluate this impact: one to study the impact of multimodal dynamics (summarized in Figure 6.5), and one to study the impact of social dynamics (summarized in Figure 6.4).

In the first study, focused on the inclusion of multimodal dynamics, as seen in Figure 6.5, the performance of the model when combining head motion and language features improves upon the univariate performance (Figure 6.3). In the second study, focused on the inclusion of social dynamics, we observe similar results, presented in Figure 6.4. We observe that dyadic models using language features improve upon the multimodal models, but the head motion features do not. However, the dyadic head motion models are improved upon the univariate models

in Figure 6.3. In general, we can observe that the bivariate models across individuals and the bivariate models across modalities improve upon the univariate models.

Ultimately, however, our goal is to model the details of the temporal behavior dynamics between modalities *and* individuals. To achieve this, we further extend the bivariate latent change score model to construct a *multiview latent change score model*. By integrating multimodal interactions and individual differences, this multiview extension offers valuable insight into the intricate patterns of therapist-client interactions, facilitating a more nuanced modeling of the factors influencing therapy outcomes. The final model is illustrated in Figure 6.1.

Representation Learning

With the model design in place, we now outline the process of training the model to effectively capture these multimodal and social behavior dynamics. The ultimate objective of the SEM framework is to minimize the difference between the covariance matrix observed in the data and the covariance matrix implied by the model. Consequently, the appropriate approximation of the covariance matrix is of vital importance for our analysis. We note that the standard calculation of the covariance matrix is suboptimal for our use case: we cannot assume that our data are normally distributed (we would expect a long-tailed distribution), nor does our dataset contain an overly large number of observations (conventional wisdom suggests that the standard calculation requires 10–20$\times$ observations as the number of observed variables; [76, 128]). For these reasons, we turn to the asymptotic distribution-free covariance estimation method.

The asymptotic distribution-free covariance matrix is calculated using Spearman's rank coefficient, a nonparametric measure of correlation based on the order of values [214], in contrast to the standard calculation which uses the normality-assuming Pearson's coefficient based on the raw values [152]. The method of asymptotic distribution-free covariance estimation has also been shown to improve the performance of covariance-based models when an analysis is limited by smaller data sets [145].

Our goal is to minimize the difference between this sample covariance matrix and the model-implied covariance matrix. The model-implied covariance matrix is calculated with

$$\Sigma_M = \Lambda(I - B_0)^{-1}\Psi((I - B_0)^{-1})^T\Lambda^T + \Theta, \tag{6.10}$$

where Λ, Θ, Ψ, and B_0 are the four parameter matrices that specify the model[1].

For an SEM with n_m measured variables and n_l latent factors, these matrices are

- Factor loadings (Λ), the regression coefficients of unobserved latent factors on observed measured variables, of shape $n_m \times n_l$;
- Residual variances of observed variables (Θ), including measurement error, of shape $n_m \times n_m$;
- Variances and covariances of latent variables (Ψ), of shape $n_l \times n_l$; and
- Causal pathways (B), representing causal relationships between latent variables, of shape $n_l \times n_l$.

The models were trained using the Adam optimization algorithm [110] with an initial learning rate of 0.01 and the weighted squared error loss function as the minimization objective. We selected the weighted squared error loss function because, unlike other common SEM loss functions, such as maximum likelihood, the squared error loss does not assume any normality of the data [114].

$$\text{loss} = (\Sigma_S - \Sigma_M)^T W \cdot (\Sigma_S - \Sigma_M) \tag{6.11}$$

In this case, the weight matrix is set to the inverse of the covariance matrix of the sample data ($W = \Sigma_S^{-1}$). Using these weights is one way to place more emphasis on data with a smaller variance and less emphasis on data with a larger variance, to reduce the impact of observations with larger errors or greater uncertainty [68].

[1]Although much of the statistical literature presents SEM analyses in the fully-specified "LISREL" notation convention, we present our model in the abbreviated "all-y" convention for simplicity and accessibility (see [80] for more information).

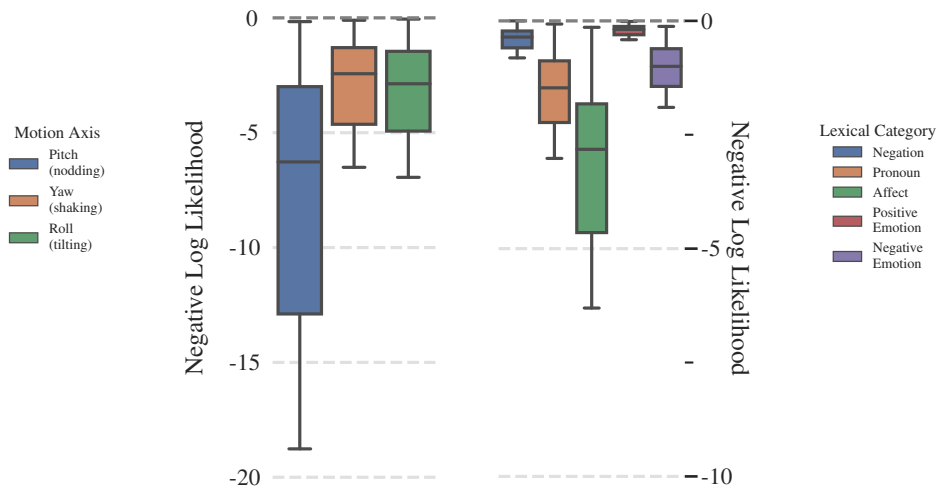


FIGURE 6.4
Average negative log-likelihood of converged dyadic models. Each model was trained upon identical features across both client and therapist.

The training procedure was repeated multiple times with random initialization. In addition to improving the robustness of the model, drawing more samples from the distribution of parameter estimates helps us to define a prior distribution for the second phase of our analysis (see Section 6.3, Experimental Setup). By approximating a range of values rather than a singular value, we can preserve data regarding the uncertainty of our parameter estimates. Retaining this uncertainty allows the model to make more informed predictions about the data. The representations generated through this method are then passed on to the predictive model (i.e., the dashed box in Figure 6.1).

Gaussian Process Regression

For our study, we have emphasized the Gaussian process (GP) regressor as our preferred predictor. It is relevant to note that, despite the 'Gaussian' name, GPs are not limited to modeling data believed to be drawn from an underlying Gaussian distribution. Instead, the name is derived from the fact that GPs learn each parameter estimate as a Gaussian distribution [162]. This is in contrast to various contemporary machine learning models that typically approximate

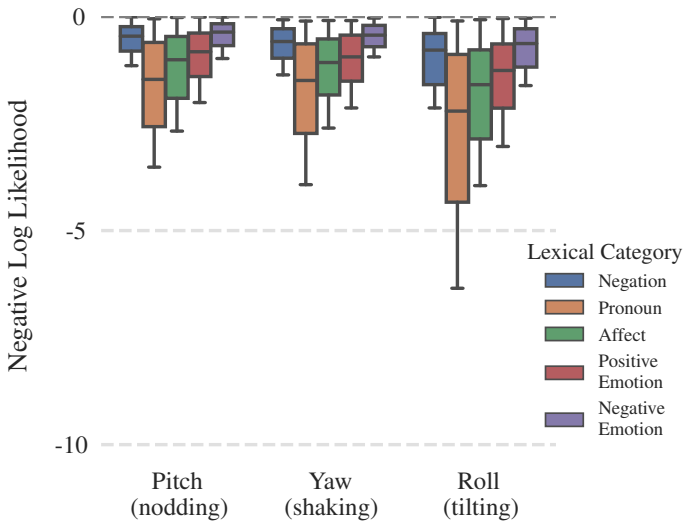


FIGURE 6.5
Average negative log-likelihood of converged bimodal models. Each model was trained upon multiple modalities within the same individual.

parameter estimates as fixed or point values. Incorporating uncertainty into a model, similar to the benefits of structural equation modeling, can improve the robustness of the model when dealing with real-world data, which are often affected by measurement error and other noise. Furthermore, Gaussian process models possess the capability to effectively approximate nonlinear associations, as they are based on kernel functions. This attribute differentiates them from other probability-based regression models, such as Bayesian regression, which are based on linear functions [63].

6.3 Experimental Setup

In addition to simply applying structural equation models to our data, we also aim to demonstrate the practicality of these features. This is achieved by presenting a comparison of various predictive models that utilize said features to forecast the working alliance ratings of both therapist and client. The data used for this analysis is derived from the behavior of therapists and clients during therapy sessions, specifically their head motion and language features. Our ultimate ob-

jective is to use these representations to improve prediction models in situations with limited data but robust domain knowledge. The results illustrate the utility of structural equation modeling as a form of representation learning for systems of behavior.

Data Set

The data used in this chapter originate from the same audiovisual recordings described in Chapter 4. The recordings used in this analysis include 266 therapy sessions, with the participation of 39 unique clients and 11 unique therapists[191]. Each therapist worked with 3 to 5 different clients, each client attending 6 to 8 sessions that lasted between 40 and 60 minutes. Therapy sessions were held in a private setting and recorded with the consent of the clients and the therapists.

Participants were recruited from a research registry, printed material advertising the study, and personal referrals. For inclusion in the study, participants were required to be between 18 and 65 years of age, meet the diagnostic standards for major depressive disorder according to DSM-5 [6], experience moderate or greater depressive symptoms (as indicated by a Hamilton Rating Scale for Depression score of 14 or higher; [79]), and be able and willing to provide informed consent. Individuals with comorbid psychotic disorders, active suicidal or homicidal ideation, chronic depressive symptoms, or current misuse of substances or alcohol were excluded from the study. Participants with suspected psychosis or active suicidal ideation with intent or a plan to harm themselves were referred to the psychiatric emergency room.

Feature Extraction: Head Motion

Head motion features were extracted from patient and clinician videos using OpenFace [16]. The extracted features represented the total degree of head motion in radians for each axis (pitch, yaw, and roll) within that time window. Data were grouped by a window size of 45 seconds, which was selected to guarantee a sufficient number of data points per session to attain acceptable statistical power in later analysis (see Section 6.2; Gaussian Process Regression).

To reduce tracking noise, two measures were implemented. First, frames that had a confidence level lower than 90% were eliminated[2] and linear interpolation was applied to fill the gaps, which was considered satisfactory given that the data were collected at a consistent rate. To further reduce tracking noise, a Savitzky-Golay filter was utilized to smooth the data, as it is recognized to be more effective than a moving average filter in maintaining the original shape of the data given its polynomial fitting [179]. Implementing these measures ensured a cleaner and more reliable data set for analysis.

Feature Extraction: Language Use

The audio recordings of the sessions were transcribed using a machine transcription service, TranscribeMe [197]. From these transcripts, we extracted various lexical categories using the LIWC tool (Linguistic Inquiry and Word Count; [154]), which has shown validity in measuring verbal dialogue and language usage in multiple domains [46, 153, 174]. For this study, we focus on the use of five particular lexical categories of language:

- *negations*, such as "no", "never", and "not";
- *pronouns*, such as "I", "them", and "itself";
- *affective words*, such as "nervous", "ugly", and "bitter";
- *positive emotions*[3], such as "happy", "pretty", and "good"; and
- *negative emotions*[3], such as "hate", "worthless", and "enemy".

Existing literature has shown that these specific linguistic categories are strong indicators of both an individual's mental well-being and interpersonal connections. Previous research has shown that overuse of negative words can cause increased tension between speakers [205]. However, negations can also be used to soften potentially adversarial or distressing statements during difficult conversations to preserve rapport [27]. The use of pronouns and positive emotion words

[2] Approximately 6% of video frames were excluded for low tracking confidence.
[3] Note that *positive emotion words* and *negative emotion words* are subcategories of *affective words*.

tends to improve the listener's perception of empathy, trust, or closeness [4, 74]. Negative emotion words can serve a similar purpose as negations: while often linked to social tension or negative communication spiraling at a broad level [11, 71], negative emotion words can also facilitate collaborative problem solving and understanding when communicated with respect and empathy [171].

Target Variable: Working Alliance Ratings

The working alliance in therapy refers to the collaborative relationship that develops between a therapist and the client throughout treatment and the degree to which they work together effectively [23]. A strong working alliance fosters trust and open communication between the client and the therapist, which is known to contribute to better therapeutic outcomes [93]. After the end of each therapy session, both the therapist and the client participants completed the therapist and client versions of the short form of the Working Alliance Inventory (WAI-SR; [84, 91]), a widely used measure of alliance in therapy. The WAI consists of three subscales that measure the three distinct components of a working alliance:

- the *goal* subscale, which evaluates the individual's belief that participants agree on the overall objectives of the treatment;
- the *task* subscale, which evaluates the individual's belief that participants agree on the steps required to achieve those goals; and
- the *bond* subscale, which evaluates the individual's emotional respect and trust for the other participant.

Each subscale consists of statements that the individual rates on a five-point Likert-type scale ranging from "seldom true" to "always true". The client version of the inventory contains 12 items, while the therapist version contains 10 items. For the purposes of this analysis, we combine the *task* and *goal* subscales due to their very high correlation: these two subscales achieve

Pearson's correlation coefficient of $r = 0.96$ between them.[4] Representative items for each subscale are presented in Table 6.1.

Baseline Models

We select a small set of popular machine learning models to compare: ElasticNet, support vector regression, random forests, and the Gaussian process regressor. We selected these algorithms for their ability to perform well on small data sets. We have particular interest in the Gaussian process regressor because it can incorporate the information about uncertainty in the parameter estimates from the structural equation model. We also compare our multiview LCSM-based feature set against other frequently-used sets of sequence features: aggregate features (entropy, mean changes, variance, etc. [41]), cross-correlation features, and the combination of aggregate and cross-correlation features.

Model hyperparameters were automatically selected using a leave-one-therapist-out approach to reduce the risk of train-test data contamination. In this approach, each therapist ($n = 11$) acted once as the test set: all sessions conducted by that therapist were designated as the test set, while all other sessions were allocated to the training set. Validation for each fold was conducted in a similar manner within the training set, with one therapist's sessions being used for validation and the remaining sessions used for training. Features were recalculated with every training run to prevent dependence on values from the test set. Prediction performance was measured using the root mean squared error (RMSE) metric. One advantage of RMSE over some comparable metrics, such as the coefficient of determination R^2, is that it is defined in the same units as the output variable — in this case, working alliance ratings — and its stability in smaller data sets.

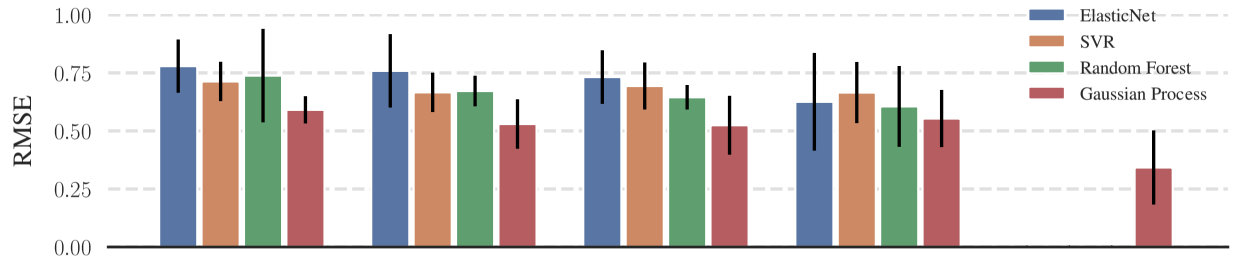
Table 6.2 presents a comparison of the test-set performance for each prediction model. Results demonstrate that the multiview LCSM features perform at the same level or surpass other commonly-used feature sets for temporal behavior analysis.

[4]For comparison, the correlation between the bond subscale and each of these factors is $r = 0.51$ and $r = 0.52$, respectively.

6.4 Results and Discussion

Our objective was to demonstrate the use of structural equation modeling as a means of representation learning for machine learning models. Our findings (Table 6.2) indicate that the models display a reasonable fit, and the features constitute valuable information for prediction tasks. To understand the decision-making process of the predictive model, we can make some interesting observations from the most predictive features selected during model training.

Table 6.3 presents the top three features, ranked by weight, for each of the target labels (task+goal ratings and bond ratings, each for both client and therapist). Some of the significant features are as expected, while others are not. For instance, observe that the client's overall use of negative emotion words (the intercept; Table 6.3c) is positively associated with the client's bond rating. Perhaps this is related to the fact that clients who are more willing to express their negative emotions to the therapist may feel a stronger connection with them, or that clients who feel more connected to the therapist may be more willing to share their negative emotions [12]. We can also observe that a stronger covariance between the use of pronouns by the therapist and the client's nodding (Table 6.3b) is linked to higher ratings of task and goal by the therapist. Pronoun words, such as "I", "you", or "they", could be related to situations in which the therapist is discussing the client ("you"). If the client nods frequently when the therapist speaks about them directly, this is related to the therapist's perception of task-related agreement. However, we also note that some as-of-yet unexplained relationships have been selected. For instance, the covariance between the client's nodding and the client's use of negative emotion words is inversely related to the client's assessment of the task and goal. Future work is necessary to suggest underlying reasons for this, but it is noteworthy to observe.



	Aggregate	Cross-Correlation	Agg. + Cross-Corr.	Multiview LCSM	Multiview LCSM w/Uncertainty
ElasticNet	0.7791 (0.2294)	0.7588 (0.3164)	0.7320 (0.2308)	**0.6255 (0.4209)**	–
SVM	0.7131 (0.1696)	0.6661 (0.1699)	0.6935 (0.2026)	**0.6653 (0.2637)**	–
Random Forest	0.7383 (0.4028)	0.6719 (0.1320)	0.6450 (0.1056)	**0.6056 (0.3484)**	–
Gaussian Process	0.5909 (0.1174)	0.5298 (0.2129)	0.5245 (0.2536)	0.5534 (0.2465)	**0.3426 (0.3193)**

TABLE 6.2
Performance metrics of predictive models: Root Mean Squared Error (mean and standard deviation). Each model was trained and tested with each of the feature sets of interest: aggregate statistics, cross-correlation statistics, combination of aggregate and cross-correlation statistics, and our multiview LCSM-based features without uncertainty information. For comparison, we also include the performance of the Gaussian Process model when it is provided with the uncertainty information from the multiview LCSM.

LCSM Parameter	Weight
Covariance: client pitch motion (nodding) & client negative emotion words	-1.3021
Transition: client pitch motion (nodding) over time	1.0398
Covariance: therapist pronoun words & client pronoun words	0.9964

(A) Client task + goal ratings.

LCSM Parameter	Weight
Intercept: client pronoun words	1.9289
Covariance: therapist pronoun words & client pitch motion (nodding)	0.9715
Intercept: therapist pronoun words	0.8118

(B) Therapist task + goal ratings.

LCSM Parameter	Weight
Intercept: client negative emotion words	1.7728
Covariance: therapist pronoun words & client pronoun words	1.2825
Covariance: therapist affective words & client yaw motion (shaking)	-1.0237

(C) Client bond ratings.

LCSM Parameter	Weight
Covariance: client roll motion (tilting) & client affective words	1.3413
Intercept: client yaw motion (shaking)	1.1930
Covariance: therapist affective words & client negative emotion words	1.0697

(D) Therapist bond ratings.

TABLE 6.3
Top three features in the Gaussian process model by average weight for each of the target labels.

6.5 Conclusion

We have presented a novel methodology for developing computational representations of behavior that integrate information from multiple modalities, individuals, and time points. Our technique builds upon an existing structural equation modeling framework. Specifically, we define a multi-view extension of the latent change score model. Our analysis indicates that this structure does fit data well in our use case, suggesting that it is indeed finding patterns in the data. We use the learned parameters of this model as input features for a secondary, predictive model, and demonstrate that the performance achieved using these features is comparable to that achieved using than many classic features for this task. Our findings demonstrate that learning features through this particular form of model training yields rich information about specific areas of uncertainty, and that integration of this knowledge into models that are equipped to handle such information improves performance further. This approach to learning representations of multimodal, interpersonal, and temporal behavior creates novel opportunities for learning about and simulating human behavior.

Acknowledgements

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Chapter 7

End-to-End Learning

In this chapter, we propose a novel framework that integrates the flexibility and predictive power of neural networks with the structural and theory-driven insights provided by structural equation modeling. Our objective is to improve the performance of data-driven predictive models, particularly in situations with limited data, by incorporating domain knowledge through theory-driven methods. While neural networks allow us to learn complex patterns and make predictions, structural equation modeling allows us to create graph models based on prior domain knowledge or hypotheses. We demonstrate that integrating structural equation modeling into a neural network during the training process can often improve the predictive performance of the model.

7.1 Data Set

The data used in this chapter originate from the same audiovisual recordings described in Chapter 4. This dataset consists of audiovisual recordings of 266 therapy sessions, as in Chapter 6. These sessions involved the participation of 39 unique clients and 11 unique therapists [191]. Each therapist worked with 3 to 5 different clients, and each client attended 6 to 8 sessions. The duration of each session ranged from 40 to 60 minutes. All therapy sessions took place in a private setting and were recorded with the consent of both the clients and the therapists.

Participants for this study were recruited through a research registry, printed material advertising the study, and personal referrals. To be included in the study, participants needed to meet the following criteria:

- Age between 18 and 65 years old,
- Diagnosis of major depressive disorder as defined by DSM-5 [6],
- Experience moderate or greater depressive symptoms (indicated by a Hamilton Rating Scale for Depression score of 14 or higher; 79), and
- Capability and willingness to provide informed consent.

Individuals with comorbid psychotic disorders, active suicidal or homicidal thoughts, chronic depressive symptoms, or current substance or alcohol misuse were excluded from the study. Participants who were suspected to have psychosis or active suicidal thoughts with intent or a plan to harm themselves or others were referred to the psychiatric emergency room.

Feature Extraction: Head Motion

Head motion features were extracted from patient and clinician videos using OpenFace [16]. These features represented the total degree of head motion in radians for each axis (pitch, yaw, and roll) within a given time window. The data were grouped using a window size of 45 seconds, which allowed for a sufficient number of data points per session to ensure acceptable statistical

power in later analysis.

To reduce tracking noise, two measures were implemented. Firstly, frames with a confidence level below 90% were eliminated and the gaps were filled using linear interpolation[1]. This approach was considered satisfactory since the data were collected at a consistent rate. Additionally, a Savitzky-Golay filter was applied to further reduce tracking noise. This filter is known to be more effective than a moving average filter in preserving the original shape of the data due to its polynomial fitting [179]. Implementing these measures ensured a cleaner and more reliable data set for analysis.

Feature Extraction: Language Use

The audio recordings of the sessions were transcribed using a machine transcription service, TranscribeMe [197]. From these transcripts, we extracted various lexical categories using the LIWC tool (Linguistic Inquiry and Word Count; 154). This tool has demonstrated validity in measuring characteristics of verbal dialogue and language usage across a variety of domains [46, 153, 174]. For this study, we focused on five particular lexical categories of language:

- *negations*, such as "no", "never", and "not";
- *pronouns*, such as "I", "them", and "itself";
- *affective words*, such as "nervous", "ugly", and "bitter";
- *positive emotions*[2], such as "happy", "pretty", and "good"; and
- *negative emotions*[2], such as "hate", "worthless", and "enemy".

Existing literature has demonstrated that specific linguistic categories can provide insights into an individual's mental well-being and interpersonal connections. Previous research suggests that overusing negative words can lead to increased tension between speakers [205]. However, negations can also be used to soften potentially adversarial or distressing statements during difficult

[1] Approximately 6% of video frames were excluded for low tracking confidence.
[2] Note that *positive emotion words* and *negative emotion words* are subcategories of *affective words*.

Goal Subscale	Task Subscale	Bond Subscale
[Therapist] and I collaborate on setting goals for my therapy.	What I am doing in therapy gives me new ways of looking at my problem.	I believe [Therapist] likes me.
[Therapist] and I have established a good understanding of the kind of changes that would be good for me.	[Therapist] and I agree on what is important for me to work on.	I feel that [Therapist] appreciates me.
We are working towards mutually agreed upon goals.	[Client] and I agree about the steps to be taken to improve his/her situation.	I feel [Therapist] cares about me even when I do things that he/she does not approve of.
[Client] and I have a common perception of his/her goals.	[Client] and I both feel confident about the usefulness of our current activity in therapy.	I appreciate [Client] as a person.
		[Client] and I respect each other.

TABLE 7.1
Sample items from both therapist and client versions of the Working Alliance Inventory.

conversations in order to maintain rapport [27]. The use of pronouns and positive emotion words has been found to enhance perceptions of empathy, trust, or closeness in listeners [4, 74]. Similarly, negative emotion words can serve a similar purpose as negations, facilitating collaborative problem-solving and understanding when communicated with respect and empathy, despite their association with social tension or negative communication spirals at a broader level [11, 71, 171].

Target Variable: Working Alliance Ratings

The working alliance in therapy refers to the collaborative relationship that develops between a therapist and the client throughout treatment, and the extent to which they effectively work together [23]. A strong working alliance fosters trust and open communication, which is known to contribute to better therapeutic outcomes [93]. At the end of each therapy session, both the therapist and the client completed the therapist and client versions of the short form of the Working Alliance Inventory (WAI-SR; 84, 91), which is a widely used measure of working alliance. The WAI consists of three subscales that measure the three distinct components of a working alliance:

- the *goal* subscale evaluates the individual's belief that participants agree on the overall

objectives of the interaction,

- the *task* subscale evaluates the individual's belief that participants agree on the steps required to achieve those goals, and
- the *bond* subscale evaluates the individual's emotional respect and trust for the other participant.

Each subscale consists of statements that the individual rates on a five-point Likert-type scale, ranging from "seldom true" to "always true". The client version of the inventory contains 12 items, while the therapist version contains 10 items. For the purposes of this analysis, we combine the *task* and *goal* subscales given their very high correlation, as indicated by a Pearson's r value of 1.96 [3]. Table 7.1 presents representative items for each subscale.

7.2 Model Definition

In this study, we introduce a novel framework that combines neural networks and structural equation modeling (SEM) for the analysis of multimodal data. This model operates by segmenting the data into temporal intervals, extracting relevant features, and generating distinct representations for each interval. These individual segment representations are then pooled to form a comprehensive overview of the data. The novelty of this framework lies in a dedicated statistical component embedded into the neural network architecture, in which the values of a designated layer are used directly as SEM coefficients. These coefficients, along with the initial input data, are evaluated for their compatibility with a domain-informed SEM structure. The performance of the framework is optimized through a combined loss function that takes into account both the fit of the SEM and the accuracy of the final prediction. While this method is versatile and can be applied to various types of data, we demonstrate its utility in the analysis of longitudinal, dyadic client-therapist relationships, as defined in Section 7.1.

[3] In comparison, the Pearson's r values describing the correlation between the *bond* subscale versus the *task* and *goal* subscales are $r = 0.51$ and $r = 0.52$, respectively.

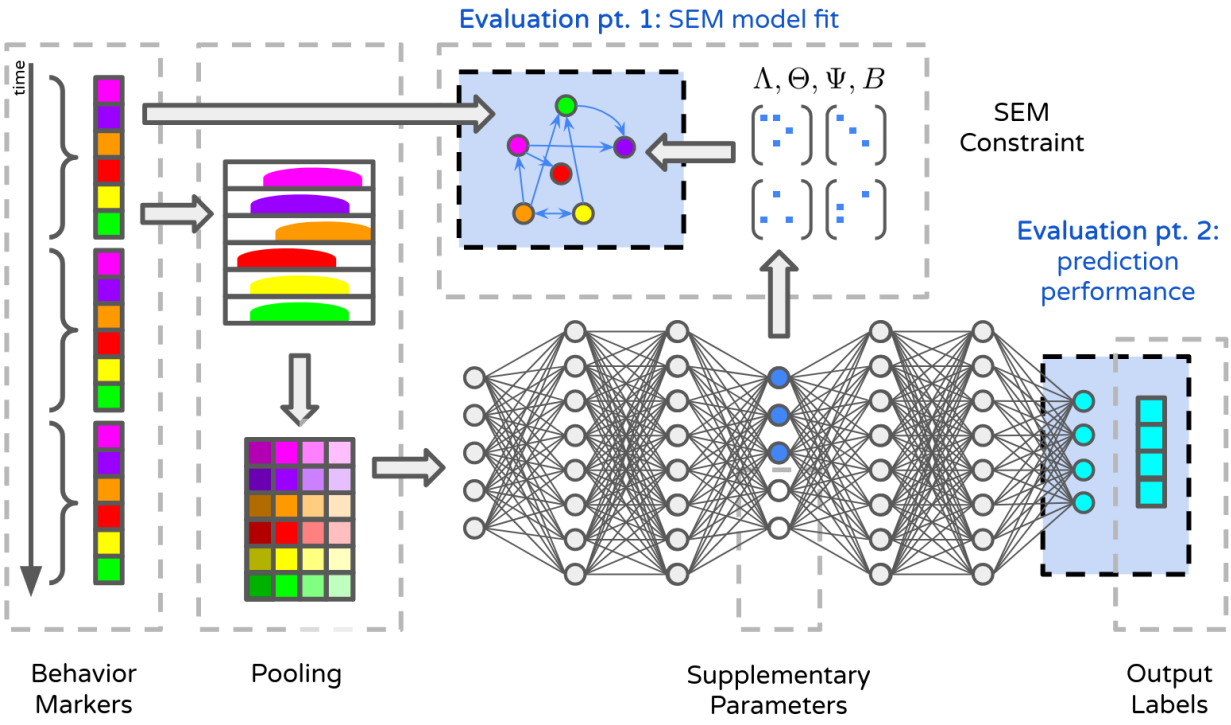

FIGURE 7.1
An overview illustration of the methodology presented in this chapter.

The unique advantage of this hybrid model lies in its dual-objective nature, which allows for the contextualization of the fitted SEM and prediction performance. The SEM fit measures the alignment between the learned representation and the observed data, while the prediction performance measures the model's accuracy and its ability to generalize to new data. By considering these two aspects together, we can gain a better understanding of how the identified structure influences the predictive power of the model.

In the absence of the SEM component, a neural network is trained to directly predict the output based on the input data, without imposing any explicit structure or relationships among the variables. The model aims to learn any possible patterns in the training data that optimize its predictive performance, which may or may not reflect the true predictive factors. However, by incorporating the SEM, an additional layer of structure is introduced to the model. The SEM represents hypothesized relationships among the variables, which are subsequently incorporated into the model's training process. This inclusion of the SEM may help the model make sense

of complex data and improve prediction performance if the SEM accurately represents the true relationships among the variables. The intersection of structural fit and prediction performance enables a more informed model.

Segmentation and Pooling

The objective of this demonstrative analysis is to examine specific aspects of therapist and client behavior, with a particular focus on head movements and language usage, and how these behaviors relate to the evolving working alliance between them. These aspects are characterized by k behavioral features, the definition of which is explained in detail in Section 7.1.

To create a consistent holistic representation of each session, every sequence is divided into multiple segments, each lasting 45 seconds. This specific duration was determined based on prior analysis in which the 45-second duration emerged as the most suitable for the particular structural equation model (SEM) we implement in this work [201] (for further detail on this structure, see Section 7.2). For each of these segments, we create a feature vector of size $2k \times 1$ that captures the characteristics of that particular time frame: k features of the client's behavior and k features of the therapist's behavior. This process yields a set of vectors in which each vector uniquely represents a distinct time segment. We pool the elements of each vector across all segments to generate $2k$ distributions, each corresponding to a different feature for an individual.

We characterize each distribution using four statistical measures:

- the *mean*, representing the average value, i.e., the most typical behavior of the individual;
- the *variance*, representing the spread of values, i.e., the consistency of the individual's behavior;
- the *skewness*, representing the symmetry or lack thereof in the distribution, i.e., whether the individual tends to behave less (positive skewness) or more intensely (negative skewness) than their typical behavior; and

- the *kurtosis*, representing the extent to which the distribution's tails deviate from the norm, i.e., how often the individual has instances of extreme behavior.

By calculating these metrics for the distribution associated with each feature, we derive a vector of dimensions $(2k \cdot 4) \times 1$, which defines a succinct representation of the entire sequence. This vector represents the overall behavioral patterns of the dyad throughout the session. Through this procedure, we aim to produce a consistent representation for the sessions studied in this particular analysis, but it is important to note that the general framework employed henceforth is highly adaptable. This framework can be effectively applied to any given set of input values that are associated with specific labels or outcomes targeted for prediction.

Structural Equation Modeling

Structural equation modeling (SEM) is a multivariate statistical approach used to analyze complex relationships between latent and observed variables [51, 127]. Generally confirmatory in nature, SEM aims to test whether a hypothesized model fits a given dataset, involving the use of several mathematical *equations* describing a hypothesized *structure* of the data. This structure defines a set of relationships between latent and observed variables, such as factor loadings, causal pathways, and covariance matrices. If the model fits the data well, its structure provides us with insight into the underlying driving behavior patterns in the data, while also taking into account measurement errors and potentially confounding factors. In general, SEM has become increasingly popular for interdisciplinary research due to its ability to capture complexity within systems without sacrificing interpretability [156, 183, 213].

While neural networks and other common machine learning techniques excel at tasks such as pattern recognition and prediction, SEM focuses on identification of the underlying structure and mechanisms of a system. One distinct advantage of SEM is that its theoretical framework allows researchers to incorporate domain-specific knowledge into the design of the model, leading to a more interpretable analysis [51]. In contrast, most classical machine learning techniques are

data-driven and do not require explicit assumptions about the relationships between variables, making them more flexible but generally less interpretable than SEM. Another important aspect of SEM is its ability to account for uncertainty. This is particularly valuable when studying complex phenomena where sources of uncertainty, such as measurement error, can significantly impact the results [114, 156]. In contrast, classical machine learning techniques often assume that the observed data is error-free, which is rarely a reasonable assumption when studying observed human behavior.

The ultimate objective of the SEM framework is to minimize the difference between the covariance matrix observed in the data and the covariance matrix implied by the model. The model-implied covariance matrix is calculated with

$$\Sigma_M = \Lambda(I - \beta)^{-1}\Psi((I - \beta)^{-1})^T\Lambda^T + \Theta, \tag{7.1}$$

where Λ, Θ, Ψ, and β are the four parameter matrices that specify the model[4]. For an SEM with $2k$ measured variables and m latent factors, these matrices are

- Factor loadings (Λ), the regression coefficients of unobserved latent factors on observed measured variables, of shape $2k \times m$;
- Residual variances of observed variables (Θ), including measurement error, of shape $2k \times 2k$;
- Variances and covariances of latent variables (Ψ), of shape $m \times m$; and
- Path coefficients (β), representing causal relationships between latent variables, of shape $m \times m$.

The primary novelty of this work lies in the fusion of these two models. The output values generated at a predetermined layer of the neural network are shaped into the four matrices of the

[4]Although much of the statistical literature presents SEM analyses in the fully-specified "LISREL" notation convention, we present our model in the abbreviated "all-y" convention for simplicity and accessibility (see [80] for more information).

SEM: Λ, Θ, Ψ, and β. It is worth noting that certain sections of these matrices are fixed and not freely estimated. In most cases, these fixed parameters are set to zero, representing the assumption that most potential relationships (out of all possible relationships) between variables do not exist. Thus, we use the layer output only to represent the non-fixed parameters in the matrices. With these estimated parameter matrices, we can calculate the model-implied covariance matrix for the SEM. We can then compare the similarity of this model-implied covariance matrix to the covariance matrix of the original input data provided at the start of the neural network.

We calculate this similarity using the weighted squared error loss function because, unlike other common SEM loss functions, such as maximum likelihood, the squared error loss does not assume any normality of the data [114].

$$\text{model fit loss} = (\Sigma_S - \Sigma_M)^T W \cdot (\Sigma_S - \Sigma_M), \tag{7.2}$$

where Σ_S is the covariance matrix of the input sample and Σ_M is the covariance matrix implied by the model. In this case, the weight matrix is set to the inverse of the covariance matrix of the sample data ($W = \Sigma_S^{-1}$). Using these weights is one way to place more emphasis on data with a smaller variance and less emphasis on data with a larger variance, to reduce the impact of observations with larger errors or greater uncertainty [68].

For this work, we utilize the SEM structure of the multiview latent change score model, as introduced in Chapter 6. We select this structure for demonstration because it has been shown to fit this type of data well and provides a satisfactory representation of the relationships within the data.

Performance and Model Optimization

The final component of the framework involves using the same free parameters mentioned above as predictors for the final target label. In this study, our target variables are the working alliance ratings from both the client and the therapist. The definition of working alliance and explanation

of these scores can be found in Section 7.1. Each individual has two scores, resulting in a total output vector of 4×1. To assess prediction performance, we can use any standard regression loss, but for this analysis, we use root mean squared error loss (RMSE).

$$\text{prediction loss} = \sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}} \tag{7.3}$$

The models were trained using the Adam optimization algorithm [110] with an initial learning rate of 0.01 and a two-part minimization objective. One part of the objective function represents the model fit, and the other represents the prediction performance:

$$\text{total loss} = \lambda \times \underbrace{\sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}}}_{\text{prediction performance loss}} + (1-\lambda) \times \underbrace{(\Sigma_S - \Sigma_M)^T \Sigma_S^{-1} (\Sigma_S - \Sigma_M)}_{\text{model fit loss}}. \tag{7.4}$$

In this case, lambda serves as a weighting coefficient to determine the balance between the model fit loss and the prediction performance loss. When lambda is close to zero, the model fit has a greater influence on the total loss, whereas a value close to one indicates a greater influence of prediction performance. The impact of different lambda values is discussed in Section 7.3.

Supplementary Parameters

While structural equation modeling can handle a certain degree of measurement error and uncertainty, it may not provide a good fit if there are factors in the data that are not included in the design of the SEM. For instance, our goal is to use SEM to capture the various dynamics of multimodal behavior, but we may not have sufficient data to incorporate personality traits in the structure, even though we believe that behavior is influenced by them. In such cases, one option is to introduce 'supplementary' parameters to the output of the first part of the network (illustrated in Figure 7.1). These parameters are still used in the second half of the network, for the prediction task, but do not correspond to any parameters of the SEM.

However, including too many supplementary parameters may prevent the SEM from capturing the signal in the data effectively. In this work, we include a regularization term in our loss function to penalize the number of supplementary parameters we add.

$$\text{total loss} = \lambda_1 \times \underbrace{\sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}}}_{\text{prediction performance loss}} + \lambda_2 \times \underbrace{(\Sigma_S - \Sigma_M)^T \Sigma_S^{-1} (\Sigma_S - \Sigma_M)}_{\text{model fit loss}} + \lambda_3 \times \underbrace{||w||}_{\text{regularization}}, \tag{7.5}$$

where w represents the vector of supplementary parameters we add. Note that in this case, we need to determine the optimal values for three weighting coefficients. While λ_1 and λ_2 can be estimated similarly as previously introduced, it is important to emphasize that we generally want λ_3 to have a significant weight. We choose to penalize the overall value of the weights of the supplementary values instead of the raw number. This is because we want to be more accepting of slight variation from the estimation of the SEM, rather than larger variation from its estimation. We discuss the influence of w and its effect on model performance in Section 7.3.

7.3 Experimental Results

We conducted a series of experiments to assess the performance of these models. First, we compare its performance with that of existing models in the same space. We also experimented with the effect of different regularization patterns by varying the weights of the previously mentioned lambdas. Finally, we also examined the effect of using different quantities of supplementary parameters on the model's performance.

Prediction Performance

We compare our approach with Gaussian process models using aggregate and cross-correlation features, as described in Chapter 4, as well as the proposed MVLCSM features from this previous work. We find that the multilayer perceptron network generally outperforms these models, but

GAUSSIAN PROCESS	
Aggregate	0.5909 (0.1174)
Cross-correlation	0.5298 (0.2129)
Agg. + Cross-corr.	0.5245 (0.2536)
MVLCSM	0.5534 (0.2465)
MVLCSM w/Uncertainty	0.3426 (0.3193)
MLP	
No Constraint	0.3190 (0.2367)
Structure Only	0.3210 (0.2352)
SEM Constraint	0.2683 (0.2070)

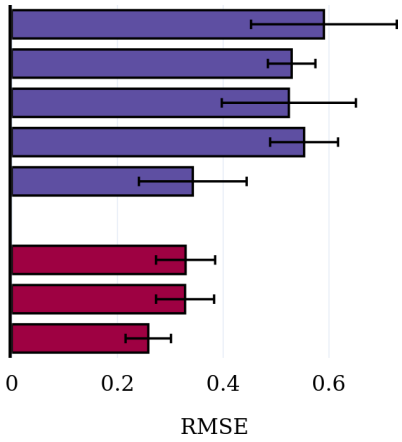

TABLE 7.2
Performance metrics of the Gaussian process models used in 6 and the hybrid models proposed in this work: mean and standard deviation of the root mean squared error (lower is better).

this performance improves further when we incorporate the constraints of the structural equation model to the model. These results are presented in Table 7.2.

This change in performance may indicate that the inclusion of the SEM in the neural network provides the model with a more structured understanding of the relationships within the data, which may in turn improve its predictive ability. This result supports the idea that incorporating domain-specific knowledge and structure into machine learning models can lead to improved performance.

Regularization Results

We also aim to understand how changing the regularization parameter affects how well our model performs. This parameter, denoted by λ (lambda), helps us balance two important parts of our model's performance: how well the model fits the hypothesized data structure and how well the overall model predicts new data. In this context, λ determines how much importance we give to the prediction part of our model, while $1 - \lambda$ determines how much importance we give to the structural fit.

The results, presented in Figure 7.2, demonstrate that when the regularization value is low,

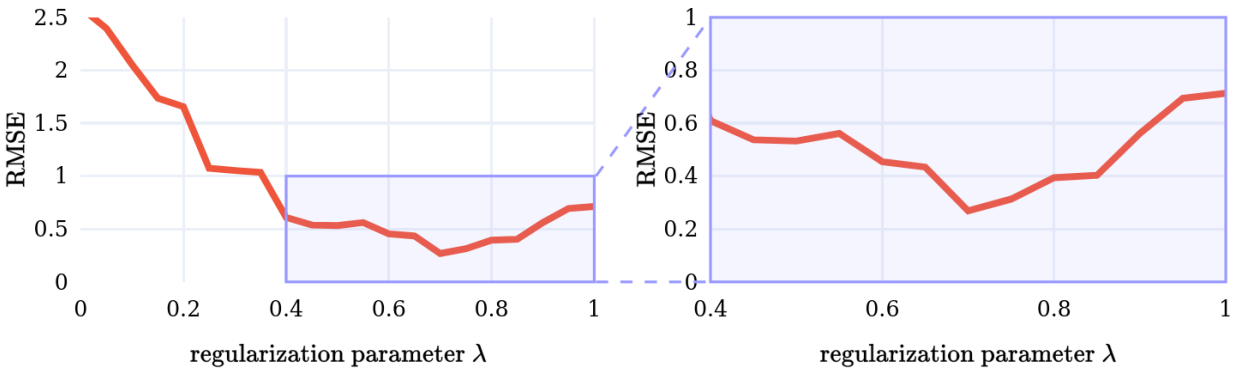

FIGURE 7.2
Model performance with varying values of the regularization parameter: root mean squared error (lower is better). Note that λ is the coefficient weighting the prediction loss; therefore, $1 - \lambda$ is the coefficient weighting the SEM fit.

the model's performance is very poor. This follows logically from the fact that a low value of λ represents a lower weight given to the prediction performance during optimization. As the value of λ increases, the performance of the model also improves, reaching its peak at approximately $\lambda = 0.70$.

This value indicates that the model performs best on test data when it places around twice as much emphasis on prediction performance ($\lambda = 0.70$) as it does on structural fit ($1 - \lambda = 0.30$) during training. This suggests that while prediction performance is the primary focus of optimization during training, placing some emphasis on fitting the structure of the data can further enhance that prediction performance when the model is later applied to test data.

Supplementary Parameter Analysis

Lastly, we examined how the number of supplementary variables affects the model's performance in situations where the SEM cannot capture all the variance itself: these supplementary variables are described in more detail in Section 7.2. We looked at different quantities of these variables in relation to the total number of structural equation modeling parameters. We discovered that performance is generally poor when few supplementary parameters are provided. However, performance improves as more are added. Peak performance is reached when the num-

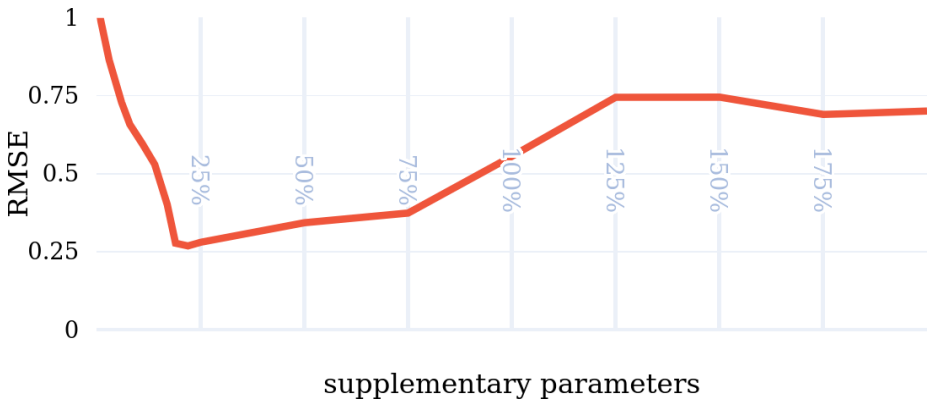

FIGURE 7.3
Model performance with varying quantities of supplementary variables, relative to the number of parameters in the structural equation model: average root mean squared error (lower is better).

ber of supplementary parameters is about 10% of the number of SEM parameters. Beyond this point, performance declines slightly but stabilizes. This result suggests that while supplementary parameters can enhance model performance by accounting for additional variability in the data that the SEM cannot account for, there is a limit beyond which these parameters may start to dilute the data structure represented by the SEM.

7.4 Conclusion

Our framework, which integrates neural networks and structural equation modeling, performs well on our prediction tasks for client-therapist interactions. The inclusion of the structural equation model provides a path to incorporate domain knowledge during model training: an advantage that is particularly useful for settings with limited data, such as recordings of client-therapist interaction. Our analyses highlight the impact of the regularization parameter and the number of supplementary variables. This model's ability to incorporate domain-specific knowledge and structure into machine learning models can potentially lead to improved performance in other tasks in the future as well.

Chapter 8

Conclusion and Future Directions

The central theme of this thesis was the critical examination of computational behavior analysis as an enhancement to the therapeutic process, with a focus on symptomatic behaviors, the development of the client-therapist relationship, and methods that enable simultaneous learning and effective modeling of these aspects. Human behavior is multifaceted, and we approached its study recognizing this complexity. We considered *multimodal* behavior dynamics, acknowledging that alongside spoken language, non-verbal cues such as gesture, facial expression, pose, and gaze also contribute to "body language". We also accounted for *social* behavior dynamics, understanding that human behavior does not exist in isolation but rather in response and reaction to the behaviors of others. These two dimensions of behavior characterize the essential underlying structure of this work: client symptom severity was principally studied in the context of multimodal behavior, while the client-therapist relationship was principally studied in the context of social behavior. Finally, we synthesized these dimensions through the development of novel *hybrid modeling* techniques. These models blend data-driven and theory-driven methodologies, allowing us to leverage the computational power of machine learning with the domain knowledge encoded within structural equation modeling.

8.1 Contributions

This thesis makes substantial contributions toward addressing three major challenges:

- **Multimodal Behavior:** We have identified and analyzed key verbal and nonverbal markers of psychotic symptom severity in participants. Through the study of spoken language, facial expression, gaze aversion, and head motion behaviors, we have developed predictive models that can estimate the severity of various symptoms and differentiate between symptom-based subtypes of schizophrenia.
- **Social Behavior:** We have explored the role of conversational turn-taking and entrainment in the development of the working alliance between a client and their therapist. Our findings reveal certain head gestures, speaking turn patterns, and linguistic entrainment behaviors that are indicative of the participants' perception of the different components of the working alliance. Based on these behavioral markers, we have developed predictive models that can accurately estimate participant-reported ratings of the working alliance.
- **Hybrid Modeling:** We have presented a novel approach to representation learning that leverages the strengths of both data-driven and theory-driven models. Our approach focuses on enhancing the performance of data-driven predictive models through the use of theory-driven statistical models to guide the representation of the data toward a domain-informed structure. Our end-to-end model combines structural equation modeling with neural networks, and we demonstrate that this approach improves the predictive performance of the model.

8.2 Future Directions

This thesis focuses on computational techniques for multimodal and dyadic modeling of client-therapist interactions. Our ultimate aim is to enhance our understanding of human behavior by improving the performance, interpretability, and scientific capability of our models, and this

thesis has taken substantial strides toward this goal. That said, there are numerous potential avenues for future research.

- **Emotion Dynamics:** Future studies could investigate the dynamics of emotion and emotional expression during therapy sessions. The emotional dynamics in a psychotherapeutic context can be complex, multifaceted, and deeply intertwined with the therapeutic process. For instance, are sessions that are characterized by particular patterns of emotional expression more or less effective for client progress? Does the emotional interplay between therapist and client contribute to the success of the therapeutic treatment, and if so, how and to what extent? How does this interaction shape the course of the therapy session and influence the relationship between them?
- **Cross-modal Dynamics:** Understanding the interplay between different behavior modalities could also offer new insights. How do verbal and nonverbal behaviors interact and influence each other during therapy sessions? Are there specific patterns of cross-modal dynamics that are indicative of therapy outcomes or the strength of the client-therapist relationship? How do these interactions change over time as the treatment progresses and the client-therapist relationship evolves? These questions could shed more light on the complex dynamics of multimodal interaction during therapy.
- **Cross-modal Congruence:** Another interesting area for future research would be the study of multimodal congruence: the degree to which different behavior modalities match or mismatch during interaction. For instance, does a therapist's verbal affirmations match their nonverbal cues? Does this congruence (or lack thereof) impact the client's perception of the therapist, or the therapeutic process, and if so, how and to what extent? Or on the part of the client — does their multimodal behavior congruence (or lack thereof) provide any insight into the client's therapeutic progress?
- **Group Dynamics:** While the majority of this thesis focused on one-on-one interaction, future research should also explore group therapy dynamics. How does a client's verbal and

nonverbal behaviors change in a group setting? How does the presence of multiple clients impact the development of the client-therapist relationship? Each client will also develop some level of relationship with each of the other clients — how do these client-client relationships impact client behavior, or the therapeutic process in general? Investigation into the complexities of group therapy will be challenging but would offer valuable knowledge into the intricacies of group interaction.

- **Conversational Analysis:** Further exploration into the structure of conversation could also offer unique insights. For instance, how do nonverbal behavior markers, such as facial expression or body language, influence the progression of the conversation? Therapeutic conversations are frequently filled with emotionally charged or uncomfortable topics — a client's nonverbal behavior during discussion of these topics could provide valuable insight into their state of mind. Such insights could also potentially assist therapists in pacing the conversation more effectively. They might identify behavioral cues indicating the client's readiness to explore challenging topics, or when they may need more time to build trust.
- **Structured Knowledge:** Future work could also work toward integration of other forms of structured domain-specific knowledge into similar hybrid models. These knowledge representations may include ontologies, expert systems, or statistical priors. For instance, ontologies could help define important relationships between particular variables, guiding the computational models to focus on these relationships during training. Another form of structured knowledge, statistical priors, could be used to incorporate expert knowledge or beliefs about the true distribution of certain variables, before any data is observed.
- **Multiple Hypothesis Testing:** In this thesis, our end-to-end models worked with a hypothesized structure that we previously validated against the data. However, how should we approach this analysis if we don't have prior knowledge about the structure of the data? Future work could explore techniques for multiple hypothesis testing in these hybrid models. Such an approach would allow the model to test and compare multiple structures

simultaneously, enhancing the model's ability to extract meaningful insights for generalizable prediction decisions.

- **Interpretability:** Another avenue worth exploring is the enhancement of interpretability for the models presented in Chapter 6 and Chapter 7. Developing new techniques and methodologies to understand the decision-making process of these models may lead to greater trust, transparency, and the ability to identify potential limitations and biases.
- **Ethical Considerations:** As we move forward in developing more advanced computational models for analysis of therapeutic interactions, it's also important to consider the ethical implications of this line of work. Future work must carefully consider issues such as privacy, consent, and potential misuse of the developed models. Moreover, we must ensure that the models do not reinforce existing stereotypes or biases.

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