WEINSTEIN, MARIANI. M.A. In Our Own Separate Words: Interpersonal Coordination and Depression in College Student Text Messages. (2021)
Directed by Dr. Michaeline Jensen. 74 pp.

Objectives: This project investigates whether interpersonal coordination of language style in written text message communication relates to past year depressive symptoms and lifetime Major Depressive Disorder (MDD) in young adults. Those who are depressed display interpersonal ineffectiveness, and interpersonal coordination is a spontaneous interpersonal process related to interpersonal engagement and effectiveness. Consistent with application of Joiner's Integrative Interpersonal Framework to interpersonal coordination, low interpersonal coordination may erode social resources that are protective against depression and in turn depression may self-propagate by decreasing interpersonal coordination. Therefore, I hypothesized that students with more experiences of depression would engage in less interpersonal coordination in their sent text messages. Because depression impacts the behaviors of others, I also expected that texting partners of those with more depression experience would also coordinate their language styles less than texting partners of those with less depression experience. **Methods:** College students at UNC Chapel Hill (N = 267) contributed all their text messages (569,172 text messages) over two weeks in 2014-2015 with all texting partners, alongside self-report surveys of mental health and other psychosocial factors. Associations between target and partner interpersonal coordination (measured as reciprocal language style matching on function words) and past year depressive symptoms and lifetime Major Depressive Disorder were tested in a series of structural equation models. Sensitivity analyses explored associations in romantic relationship dyads and in a subset of more standard English-speaking dyads. **Results:** In primary analyses, contrary to hypotheses, people who had more depression experience and their partners did not tend to coordinate their language style less. I observed the same lack of significant associations in a sensitivity analysis among only romantic relationship dyads. However, the pattern was different among dyads that conformed more closely to standard English (as opposed to heavily relying on text abbreviations and alternate spellings). In this subgroup, students with more past year depressive symptoms and lifetime MDD coordinated *more* (opposite the hypothesized direction of effect). **Conclusions:** Interpersonal coordination as indexed by reciprocal language style matching of function words is difficult to capture in text message conversations, and we did not see support for our hypothesis that people with more depression experiences (and their partners) would coordinate less. Rather, sensitivity analyses revealed that students with more depression experiences may engage in more interpersonal coordination in text messages. Future studies should examine whether people who are in a current MDD episode, in remission, or who have depressive symptoms coordinate *more* than non-depressed, never-depressed, and less depressed people. Future studies should also examine alternative ways to measure interpersonal coordination in digital communication.

IN OUR OWN SEPARATE WORDS: INTERPERSONAL COORDINATION AND DEPRESSION IN COLLEGE STUDENT TEXT MESSAGES

by

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A Thesis

Submitted to

the Faculty of The Graduate School at

The University of North Carolina at Greensboro

in Partial Fulfillment

of the Requirements for the Degree

Master of Arts

Greensboro

2021

Approved by

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DEDICATION

To Shirley, who inspires me to live with purpose and zest, to my mama who deserves credit in all my accomplishments, and to Jeffrey, whose guidance has been invaluable.

APPROVAL PAGE

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ACKNOWLEDGEMENTS

I would like to thank my advisor Dr. Michaeline Jensen who has been not only an exceptional research mentor but also an advocate and encourager. I would also like to thank my committee members for their guidance. Thanks to the IRL lab family for feedback, and especially to Michael Puerto who generously shared his time and expertise in data science to help me run rLSM in our text message dataset. Writing group and writing buddies, thank you. Dear friends, thank you. Family, nothing on earth matters more to me. Familia, nada en la tierra me importa más que ustedes.

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CHAPTER I: INTRODUCTION

Introduction

Depression is an increasingly common challenge among college students, with considerable public health impact (Center for Collegiate Mental Health, 2020). About one fifth of college students (11.6% of males and 22.4% of females) report having been diagnosed with or treated for depression in the past year (American College Health Association, 2019). Over the 9-year history of the Center for Collegiate Mental Health's 2019 annual report, depression rates have consistently been rising, second only to anxiety in terms of number of students impacted. Onset of depression during the college years is potentially precipitated by the stressful transitions from high school to college and to adulthood (Eberhart & Hammen, 2006). In young adulthood, interpersonal problems predict onset of depressive disorder and increase of depressive symptoms over time (Barnett & Gotlib, 1988; Eberhart & Hammen, 2006; Hames et al., 2013; Hamilton et al., 2016; Lewinsohn et al., 1994), whereas positive relationships are protective (Eberhart & Hammen, 2006; Goodman et al., 2019; Joiner & Metalsky, 1995). Relationships, good or bad, influence success at meeting developmental tasks during the transition to adulthood (Schulenberg et al., 2004).

Depressed people often show deficits in interpersonal skills, and an interpersonal skill that might be disrupted in depression is interpersonal coordination. I will investigate whether interpersonal coordination of language style in written text message communication relates to past year depressive symptoms and a lifetime diagnosis of Major Depressive Disorder in young adults. Consistent with Joiner's Interpersonal Framework, I hypothesize that individuals with more experiences of depression engage in less interpersonal coordination of language style in their sent text messages, and that their texting partners also coordinate their language style less.

Interpersonal Effectiveness and Depression

A long body of research has consistently demonstrated that depressed individuals are less effective interpersonally than non-depressed individuals, across a variety of methods and study designs (Segrin, 2000). For example, depressed psychiatric inpatients displayed lower observationally coded social skills than non-depressed inpatients (Haley, 1985). Likewise, in observational coding of a waiting-room interaction among college students, depressed college students displayed several types of social skills deficits (compared to non-depressed students), including more negative self-statements and more unsolicited self-disclosures in response to standardized confederates (Jacobson & Anderson, 1982). A similar finding emerged when using self and other report: Depressed interlocutors were rated lower and rated themselves lower than non-depressed people on social competence (Lewinsohn et al., 1980).

More recent studies have continued to document associations between depression and poor social skills: In a cross-sectional study of college students, lower social skills in conversation (social expressivity, social control, and social sensitivity) were related to more depressive symptoms (Moeller & Seehuus, 2019). Likewise, medical residents displaying higher depression also self-reported lower social skills using a detailed inventory of retrospective frequency of behaviors (Pereira-Lima & Loureiro, 2015).

These early cross-sectional studies and recent conceptual replications informed efforts to parse the directionality in this association between depression and interpersonal effectiveness. Potential pathways are that deficits in interpersonal effectiveness predate depression (serving as a risk factor and potential preventive intervention target), the experience of depression undermines interpersonal effectiveness during a depressive episode (serving as a symptom or time-limited consequence), and/or a history of depression may have lasting impacts on later social processes (with interpersonal ineffectiveness serving as a long-term outcome). In fact, studies tend to support all three of these potential pathways to some extent (Eberhart & Hammen, 2006) suggesting that deficits in interpersonal effectiveness are an important factor in the etiology, maintenance, and consequences of depression.

Interpersonal Skills as a Risk Factor for Depression

The potential that interpersonal deficits predate depression is expressed in the social skills deficit vulnerability model (Segrin, 2000; Segrin & Flora, 1998) which predicts that poor social skills minimize opportunities to acquire social support, which in turn leads to depression. Some studies have corroborated this model by showing that a decrease in positive interactions mediates the link between social skill deficits and depression (Cooley et al., 2010; Segrin & Rynes, 2009). However, evidence that social skills deficits lead to depression is mixed, and the most rigorous studies have not always supported this association (Hames et al., 2013). For instance, in one longitudinal study, measures of social skill (perceived interpersonal competence and problem-solving skills) did not predict depressive symptoms (Eberhart & Hammen, 2006). Among 12 longitudinal studies reviewed, there was little evidence that social skill deficits are *antecedents* of depression (Segrin, 2000).

Current Depressive Symptoms Fluctuate with Interpersonal Ineffectiveness

Several studies suggest within-person associations (that when people are depressed, they exhibit interpersonal ineffectiveness, compared to when they are not depressed). For example, on days when adults with Major Depressive Disorder reported more talking and less being alone they also reported less end-of-day depressive symptoms over and above their previous day depressive symptoms—a lagged effect suggesting that more interpersonal activity reduced depressive symptoms (Snippe et al., 2016). Similarly, days on which newly-wed maritally distressed women reported more symptoms of depressed mood tended to be days on which they also reported less marital happiness, and this association was even stronger for women who were more depressed or more maritally distressed than others in the sample (Smith et al., 2012). In non-clinical samples, on days when people with more depressive symptoms interacted positively with others, they reported as much wellbeing and sense of belonging as people with fewer depressive symptoms, but on days when they did not interact positively with others, they reported less wellbeing and sense of belonging than people with fewer depressive symptoms (Steger & Kashdan, 2009). Within a day, interacting with others improves mood, positive mood encourages interactions with others, or both. In any case, individual and relational wellbeing fluctuate together on a day-to-day basis.

Longer-term longitudinal studies show similar associations. An 8-year longitudinal study found that interpersonal sensitivity (reporting feeling rejected or criticized by others, on the Inventory of Depressive Symptomatology) tended to be high among those who were experiencing a major depressive episode at the first wave but declined steeply 1 year later and continued to decline over the next 8 years, along with overall symptoms of depression. This suggests that interpersonal skills and relationships may improve over time when depression remits (van Eeden et al., 2019).

History of Depression has Lasting Impacts on Interpersonal Effectiveness

Even for those whose depression has remitted, there is some evidence that interpersonal problems persist, such as poorer relationships with spouses, children, friends and extended family (Hammen & Brennan, 2002). These relationship difficulties may be related to skill deficits. Consistent with this possibility, women who were currently or previously depressed showed worse interpersonal problem solving in response to hypothetical vignettes of marital conflict, compared to never-depressed women (Rehman et al., 2013). Individuals who had remitted from a depressive episode over the course of psychotherapy showed improved social cognition compared to their acute depressive episode; nevertheless, their social cognition in remission was not as high as healthy control individuals in most areas. This slight persistent deficit could be a vulnerability factor for relapse when faced with complex interpersonal stressors (Ladegaard et al., 2016). Even in remission, individuals with prior depression may engage in stress generation (i.e. contribute to negative life events, Hammen, 1991) particularly through unskillful interpersonal behaviors (Chun et al., 2004; Hammen & Brennan, 2002; Shih & Eberhart, 2008).

Interpersonal Ineffectiveness in Depression Impacts Partners' Interpersonal Effectiveness

Not only do depressed people behave differently than non-depressed people in interpersonal relationships, but their partners do as well. Partners of those with depression also interact in less effective ways. For example, Knobloch-Fedders and colleagues (2013) coded the interpersonal behavior of depressed and non-depressed couples in lab-based conversation tasks on dimensions of focus, affiliation, and interdependence. They found that the interpersonal behavior of depressed individuals did not differ from nondepressed individuals (surprisingly), but the behavior of the partners of depressed people differed from partners of non-depressed people. Namely, partners of people with a history of depression were more hostile and partners of those with higher depressive symptoms were more submissive than partners of people without a history of depression. Similarly, husbands of women who are more depressed post-partum engage in less dyadic coping (Alves et al., 2018).

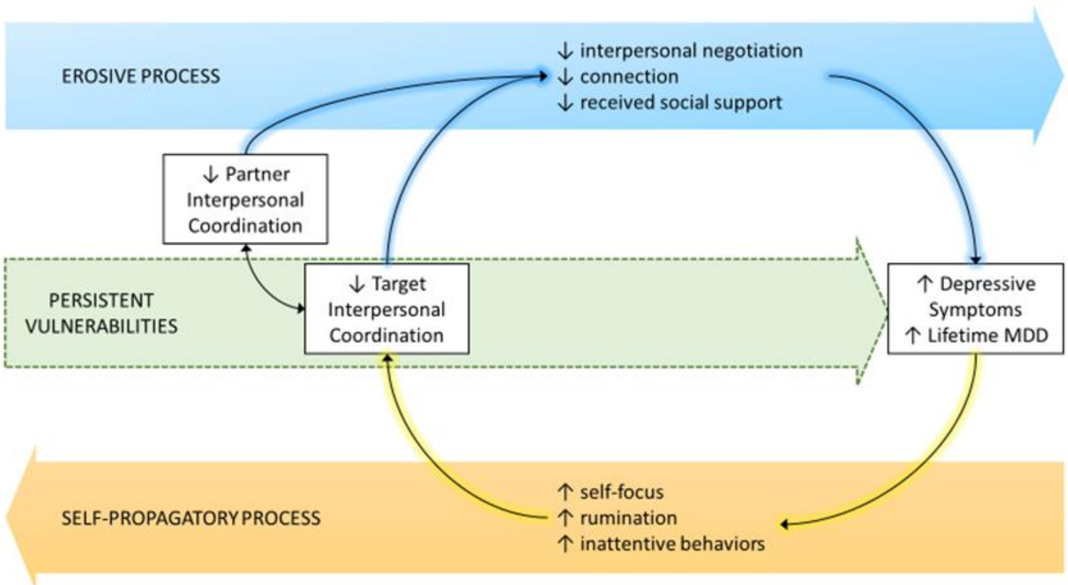
In a sample of adolescent mothers and daughters, Milan and Carlone (2018) studied how each person's symptoms predict her own and her partner's relational behaviors (warmth, hostility, communication) and whether those behaviors in turn predict depression one month later. They found that when daughters had higher depressive symptoms, mothers exhibited more negative relational behavior (e.g., hostility) during interactions (a partner effect of daughter depression on mother behavior). However, when mothers had higher depressive symptoms, daughters did not exhibit different relational behaviors over and above their own depressive symptoms (no partner effect of mother depression on daughter behavior). These studies indicate that in several kinds of close dyadic relationships (but maybe not in both directions of hierarchical relationships like mother → daughter), depression of the target can impact the interpersonal behavior of a relationship partner. Links between interpersonal effectiveness and depression have been most pronounced in close relationships such as romantic partnerships, close friendships and parent-child relationships but have also been observed to an extent in other relationships, even among strangers (Baddeley et al., 2013; Nezlek et al., 2000; Segrin & Flora, 1998).

Theories of Interpersonal Processes and Depression

Several prominent theories recognize interpersonal processes in depression (Coyne, 1976; Joiner, 2000; Lewinsohn et al., 1980). Coyne (1976) posits a cycle whereby depressed individuals engage in unskillful behaviors that elicit rejection, are rejected, and in turn feel more depressed. Lewinsohn (1980) theorized that depression is characterized by an excess of negative reinforcement and a scarcity of positive reinforcement, partially social: Social skill deficits preclude depressed individuals from accessing social reinforcement and promote negative situations. These theories suggest that depressed individuals and their partners will display indicators of problematic relationship processes (though they differ somewhat in proposed mechanisms).

The Integrative Interpersonal Framework for Depression and Its Chronicity (Joiner, 2000), which guided hypotheses in the present study, integrates prior theories. In this framework, Joiner (2000) organized interpersonal processes that contribute to the maintenance of depression into persistent vulnerabilities (which predispose towards depression or interpersonal behaviors that maintain depression), erosive processes (which decrease protective behaviors/ resources), and self-propagating processes (which increase unhelpful psychological features and behaviors). Joiner's perspective highlights that depression impacts both stable/global and specific interpersonal processes, and interplay among all these factors worsens depression. Results of previous studies (summarized below) have spoken to the role of each of the processes in Joiner's framework (persistent vulnerability, erosive, and self-propagatory) regarding interpersonal skills and depression. We use the Joiner framework to guide our construction of a model (summarized in Figure 1) that captures potential associations between depression and one specific manifestation of interpersonal effectiveness— the ability of a target and partner to "link-up" with one another during conversation (interpersonal coordination).

Figure 1. Application of Joiner's Integrative Interpersonal Model to Interpersonal Coordination and Depression



Note. This is a depiction of Joiner's Integrative Interpersonal Framework for Depression and its Chronicity (Joiner, 2000; Hames et al. 2013) applied to interpersonal coordination. This framework posits three processes that contribute to the etiology and maintenance of depression: persistent vulnerabilities (interpersonal deficits are stable and contribute to depression risk), erosive processes (interpersonal deficits erode protective factors against depression), and self-propagation (depression contributes to interpersonal deficits). Applied to interpersonal coordination, we list mediators that may be implicated in erosive and self-propagatory processes. Literature does not consistently suggest that interpersonal skills are a persistent vulnerability, and this is indicated by a dotted line. Our cross-sectional study measures the association between interpersonal coordination and depression but cannot elucidate the specific processes involved.

Summary of Interpersonal Processes in Depression

In all, depression (at the level of negative mood, depressive symptoms, and clinical disorder) seems to be related to interpersonal ineffectiveness (operationalized in many ways) and understanding this link may give insight into etiology, maintenance, and relapse in depression. Literature thus far suggests that some interpersonal effectiveness deficits might predate depression (persistent vulnerability), that depression widely disrupts interpersonal effectiveness (self-propagatory), and that even in those with remitted depression interpersonal ineffectiveness that may be a remnant of prior episodes contributes to interpersonal stress and risk for relapse (erosive). Furthermore, the interpersonal ineffectiveness of a depressed person appears to impact the interpersonal effectiveness of others. These effects appear across multiple types of relationships. The present study focuses on one specific aspect of interpersonal effectiveness: interpersonal coordination.

Interpersonal Coordination as a Key Tool for Connection

Interpersonal coordination encompasses several related constructs (i.e. mimicry, synchrony, coregulation, matching, mirroring, convergence, and accommodation) that all capture the extent to which interactors engage in the spontaneous coordination of behavior, emotions, thoughts and physiology (Bernieri & Rosenthal, 1991; Burgoon et al., 1995). Interpersonal coordination is generally associated with the quality of interactions as well as overall relationship satisfaction across development, relationships, and various operationalizations. On neural levels and starting in infancy, coordination helps humans understand and empathize with the actions of others (Pickering & Garrod, 2006). When people exhibit high interpersonal coordination, they report more interpersonal connectedness (e.g. liking, affiliation, and feelings of closeness and similarity), whereas when there is little coordination between partners, they report opposite perceptions of the interaction and show physiological signs of stress (Kouzakova et al., 2010; Niederhoffer & Pennebaker, 2002). When there is more interpersonal coordination, people are also more likely to help one another (Niederhoffer & Pennebaker, 2002). People may employ coordination to improve interactions/relationships; indeed, when people feel rejected, they tend to respond temporarily with more coordination, which sometimes enhances their belonging (Aguilar et al., 2016; Lakin et al., 2008). Overall, there is broad evidence that interpersonal coordination reflects and facilitates positive interactions, although there is increasing evidence that this is through interpersonal engagement, and not by directly fostering rapport (Niederhoffer & Pennebaker, 2002; Gonzales et al., 2010).

Theories of Interpersonal Coordination

Theories about interpersonal coordination explain why coordination occurs. The interactive alignment account of dialogue (Pickering & Garrod, 2004) suggests that for conversations among close and equal partners, alignment is the primary motive of conversation, and results in mutual understanding. Communication accommodation theory (Giles et al., 1991) says that coordination is driven by goals to regulate interpersonal distance: Subconsciously, people coordinate more to increase closeness and coordinate less to increase distance. Partner-specific adaptations theory (Brennan & Hanna, 2009) says that coordination results when people intentionally adapt to one another to grow common ground. Synergies theory (e.g., Dale et al., 2013) states that coordination arises organically to promote effective interpersonal function. All these theories, including the interactive alignment theory, are consistent with our view of interpersonal coordination as an indicator of interpersonal effectiveness.

One theory stands out for its parsimony in explaining not just *why* coordination occurs but *how* for linguistic coordination. We find the interactive alignment account most useful for detailing how coordination at various linguistic levels (including lexical and syntactic levels relevant to language style matching) occurs via a spontaneous, low-effort cognitive process. Briefly, the interactive alignment account of dialogue is a proposed cognitive (psycholinguistic) mechanism by which partners in a dialogue prime one another at every linguistic level as they develop an aligned representation of the situation that they iteratively correct. It is proposed that this process characterizes most everyday conversations, and only rarely do people engage a more intentional and effortful process (for more detail see Pickering & Garrod, 2006). Building on the interactive alignment account, Ireland et al. (2011) propose that interpersonal coordination is a result of closely attending to one's interaction partner. This attention can occur during positive or negative valence interactions, and in any case, it fosters a sense of engagement. Consistent with this proposed mechanism, coordination in language style of chatroom conversations increases when participants are asked to pay close attention to their conversation partner (Tausczik, 2012). This theoretical understanding of how coordination occurs informs our view that depression might disrupt coordination by disrupting attention.

Forms of Interpersonal Coordination

Interpersonal coordination occurs in physiology, emotions, non-verbal behavior, and multiple forms of communication. Physiological and affective synchrony occurs in young adults with friends (Cook, 2020), romantic partners (Coutinho et al., 2019; Helm et al., 2012) and parents (Amole et al., 2017; Lougheed, 2020). Many studies have examined interpersonal coordination in non-verbal behaviors (e.g., mirroring a partner's body posture), which starts in infancy (Niederhoffer & Pennebaker, 2002) and may help children develop social-cognitive skills (Tausczik & Pennebaker, 2010).

This literature on non-verbal interpersonal coordination is complemented by a literature on verbal coordination in conversations. Verbal interpersonal coordination can be indexed either based on what people say (content) or how they say it (style). A number of studies have examined coordination in semantic content (Babcock et al., 2014). However, a weakness of measuring coordination in content is that the process of interpersonal coordination (adapting to the pattern of another person) is confounded with similarity in the interests or vocabularies of conversation partners (Niederhoffer & Pennebaker, 2002).

Language *style*, in contrast, refers to aspects of language other than semantic content. For example, when people converge dialects and accents they perform better as a team (Kozlowski, 2018; Kozlowski & Ilgen, 2006). Function words are especially apt for capturing alignment in style that is separate from content, because a small number of function words make up over 60% of the words people say and carry little content on their own (Chung & Pennebaker, 2011). Although coordination of function words may be driven partly by priming (Ireland et al., 2011), other processes such as regulating interpersonal distance (Giles et al., 1991) may also be at play. Interpersonal coordination of function words was first explored by Niederhoffer & Pennebaker (2002) and is dubbed Language Style Matching (LSM). Studies so far have examined LSM and its associations with relational outcomes in a variety of relational contexts, including business, therapeutic, and intimate relationships.

In the context of psychotherapy, higher LSM in transcribed therapy sessions is associated with the therapist being rated as more empathic by coders (Lord et al., 2015). Another study suggested a bidirectional association of LSM and depression in therapy: In a small pilot study of depressed substance-using mothers, higher depressive symptoms prior to treatment predicted lower LSM in client-therapist dyads, and less LSM predicted posttreatment distress (Borelli et al., 2019). A third study showed that LSM can capture high engagement in the context of conflict: More LSM occurred prior to ruptures in fictional therapy (Aafjes-van Doorn & Müller-Frommeyer, 2020). In the romantic dating context, LSM in lab-based speed dating was linked with actual relationship initiation among interactors (Ireland et al., 2011). In business settings, more LSM evident in videotaped employer-employee performance appraisal interviews related to employees perceiving the managers as more empathetic (Meinecke & Kauffeld, 2019), LSM over instant messenger related to higher engagement during business negotiations (Ireland & Henderson, 2014), and LSM in virtual and in-person small teams related to work performance and group cohesion (Gonzales et al., 2010).

A much less studied medium for interpersonal coordination is written conversation, particularly LSM via technology, which is important for communication in the digital age. The original paper on language style matching included two experiments using internet chat rooms with scripted topics among strangers in the laboratory (a highly artificial relationship). Participants exhibited high LSM, but LSM did not relate to self-reports or coder reports of how well the conversation partners got along—consistent with the view that LSM indexes engagement and effectiveness but not directly rapport (Niederhoffer & Pennebaker, 2002). In another laboratory, LSM in small work groups held by instant messenger was related to degree of *engagement* in the group project, although not to how much participants *liked* one another (Gonzales et al., 2010). Other studies have begun to exploit the potential to capture naturalistic interactions via technology: In instant messages between dating college students gathered over 10 days (1,000 words on average per person), couples with more LSM had higher odds of still being together 3 months later (Ireland et al., 2011). More intensive forms of online communication (more conversation over more time), in semi-public contexts, have also been related to relationship connectedness: In responses to health bloggers, LSM of comments predicted perceived social support from the blogger (Rains, 2016) and in breast cancer support groups, comments with more LSM in response to self-disclosure contained more self-disclosure (Malloch & Taylor, 2019).

Taken together, evidence from these diverse fields and various operationalizations of LSM (Müller-Frommeyer et al., 2019; Niederhoffer & Pennebaker, 2002) across forms and contexts of communication supports the notion that linguistic style matching is a meaningful form of interpersonal coordination. Most often it seems that LSM reflects positive relationship outcomes, although several studies indicate the LSM is not simply a measure of liking but instead reflects how much partners are attending to and engaging with one another. Additionally, these studies show that LSM occurs in technology-mediated written communication with people across the spectrum of relationship closeness, and that it predicts outcomes such as group cohesiveness, emotional self-disclosure, perceived social support, and relationship stability. Our study builds on these previous approaches by using LSM to examine interpersonal coordination in intensive, dyadic, private, and naturalistic conversation (for the first time via text messages to all conversation partners over two weeks).

Interpersonal Coordination and Depression

Some of the social skills deficits that accompany depression can be described as deficits in interpersonal coordination (Sloan et al., 2002). For instance, looking away is a failure to coordinate gaze, and monotonous speech is a failure to modulate speech in response not only to the topic but to the conversation partner. Only a few studies have explicitly targeted the link between interpersonal coordination (or its various aliases) and depression. Experimental studies in the domains of nonverbal coordination and affect found that induced negative affect led to decreased facial mimicry of all types of emotions (Likowski et al., 2011) and depressed people mimic both sad and happy facial expressions less than non-depressed controls (Wexler et al., 1994). In an observational coding paradigm, people in remission from depression who coordinated non-verbal behaviors less with an interviewer were more likely to relapse in the next two years (Bos et al., 2006). Consistent with effects observed for social skills in general, this indicates that lower coordination is concomitant to depression (potentially via a self-propagatory process since the inability to respond to positive emotion might maintain negative emotion) and may be a risk factor for relapse (over time eroding protective social resources).

Interpersonal coordination plays a role in the developmental pathways to and intergenerational transmission of depression. Depressed mothers coordinate less with their infants (especially in gaze), suggesting that depression interferes with coordination even in the biologically and affectively intimate mother-child relationship (Granat et al., 2017; Kudinova et al., 2019). In addition, not experiencing moments of coordination with a mother predicted signs of withdrawal from infants (e.g. looking away from mother) over several months (indicating that the infants also participated less in coordination), and these infants experienced more internalizing symptoms across the first decade of their lives (Priel et al., 2019). Low interpersonal coordination in infancy contributes to persistent vulnerabilities to depression, potentially by disrupting attachment, cognitive development, and parent-child communication (Beebe et al, 2000, 2008).

In adolescence, mothers and daughters who both had depression showed almost no vagal activation (indicative of social engagement) during pleasant and unpleasant conversations, and their blunted responses were slightly negatively correlated (when one engaged, the other withdrew); in contrast, among non-depressed dyads, both mother and daughter showed vagal activation, and their responses were positively correlated (both engaged with one another, even in conflict conversations; Amole et al., 2017). Taken together, these studies suggest that adults who are depressed coordinate less with their children, and that these children are also at risk of coordinating less and developing internalizing symptoms. This is an illustration that the depression of a target impacts the interpersonal behaviors of their partner.

Interpersonal coordination in depression has been studied in the context of the therapist-client alliance. A recent systematic review of interpersonal coordination in psychotherapy included twelve of these studies of psychotherapy for depression and found that increased coordination between depressed clients and therapists predicts improvement in client depressive symptoms (Wiltshire et al., 2020). For example, more interpersonal coordination (as measured by LSM) during initial interviews between a clinician and a depressed client predicted more improvement during treatment while controlling for baseline severity of depression (Lord et al., 2015). Depressed clients tend to coordinate with therapists less than anxious clients at the outset of therapy, but coordinate more over the course of therapy (Paulick et al., 2018). In sum, interpersonal coordination appears to be malleable with therapy, and therapy appears most effective for those who coordinate more at the outset and throughout therapy, suggesting that low coordination may erode the ability to elicit or benefit from social resources.

Although low interpersonal coordination seems to erode social resources, it is not always eroded by depressive episodes. One study tested whether interpersonal coordination decreases with more episodes of depression by measuring coordination in the discharge interviews of people after treatment for their first or subsequent depressive episode, but did not find evidence that deficits in interpersonal coordination accumulate across episodes (Bouhuys & Sam, 2000).

One concern in this literature is that the psychotherapeutic relationship might be unique. However, there is some evidence that interpersonal coordination is not specific to psychotherapeutic tactics that explicitly involve coordination, such as reflecting: Language style matching related to outsider ratings of clinician empathy beyond what was predicted by use of reflecting (Lord et al., 2015). The therapeutic relationship is just one example of the interplay between interpersonal coordination and depression via social interactions.

I am aware of only one (quite relevant) study that has examined depression and interpersonal coordination measured by LSM in written, computer-mediated communication (Baddeley, 2012). In a doctoral dissertation, Baddeley (2012) compared the written, organic email communications of 30 women—who included women with Major Depressive Disorder (MDD), women in remission from MDD, or never depressed women— on their degree of written interpersonal coordination as indexed by LSM in sent and received emails with 10 close contacts of choice (friends, family, or romantic partners). Findings revealed that women in remission from MDD were the most likely to coordinate language style, and the difference between the never-depressed and actively depressed women was not statistically significant. This study also tested longitudinal associations among interpersonal coordination, severity of depressive symptoms, and extent of social support and found that more email-based interpersonal coordination during remission did predicted stronger social support later (the same trend emerged for emails sent during depressive episodes, but was not statistically significant; Baddeley, 2012). Overall, these findings may suggest that interpersonal coordination plays an enhanced role in modulating social relationships for individuals with a history of depression, since coordination during remission was elevated compared to non-depressed controls and best predicted the social support during subsequent MDD episodes.

The absence of a significant difference in the coordination of actively depressed versus never-depressed women was surprising based on the theory and evidence laid out in this paper—which suggests that low interpersonal coordination would be associated with more depression. However, we believe that the methodological limitations of Baddeley (2012), including the relatively small number and variety of individuals and relationships, warrant a replication without changing the hypothesis that lower coordination will relate to more depression. The present study seeks to extend these findings by examining whether a lifetime history of major depressive disorder and severity of past-year depressive symptoms are related to interpersonal coordination in language style, this time in text message communication.

Application of Joiner's Integrative Interpersonal Framework to Interpersonal Coordination

Although interpersonal coordination has not yet been formally considered in Joiner's framework, the framework elucidates how deficits like interpersonal coordination might arise from and contribute to depression. Interpersonal coordination fosters belonging, empathy, and overall interpersonal effectiveness (Aguilar et al., 2016; Gonzales et al., 2010). Thus, low interpersonal coordination over time may erode relationship quality and social support that are protective against depression (Segrin et al., 2016). Depression may also self-propagate by decreasing interpersonal coordination via distinctive features of depression including rumination (Aldao et al., 2010; Nolen-Hoeksema et al., 2008) and self-focused attention (Brockmeyer et al., 2015). These tendencies are directly in conflict with attending to the behaviors and emotions of another person—the cognitive process that appears to spontaneously give rise to interpersonal coordination (Tausczik, 2012). Therefore, these processes may lower coordination, which in turn increases interpersonal problems that precipitate and maintain depression (Hames et al., 2013). These theorized processes are summarized in Figure 1. Although this initial investigation did not directly test the theorized self-propagatory and erosive pathways driving the predicted linkages between interpersonal coordination and depression, it tested whether past year depression symptoms and lifetime MDD are associated with less interpersonal coordination (to potentially serve as a building block for future research on mechanisms of this hypothesized association).

The Present Study

The present study improved upon Baddeley's (2012) design by utilizing a much larger sample (267 vs. 30, with associated increases in power) and examined both the target and their partners' levels of interpersonal coordination (acknowledging the dyadic nature of interactions) in text message communications (one of the most frequent mediums of communication among youth today). Additionally, it included all text messages exchanged with all relationship types, rather than a subset of conversation partners, and calculated LSM at the level of turn-by-turn matching which might be more sensitive to interpersonal dynamics. Specifically, I asked, is interpersonal coordination (as measured by LSM) in text message communications related to depression experiences (as measured by self-report of past year depressive symptoms and qualifying for lifetime MDD)? My hypotheses were as follows:

1. Consistent with evidence suggesting that current (or here, recent) depression can undermine interpersonal effectiveness (a self-propagatory process), I hypothesized that target participants with higher past year depressive symptoms would exhibit less interpersonal coordination in their sent text messages.
2. Consistent with evidence suggesting that interpersonal ineffectiveness may occur for those with a history of MDD even during remission (due to persistent vulnerabilities or erosive processes), I hypothesized that targets with lifetime history of MDD would tend to coordinate less in their sent text messages.

3. Furthermore, consistent with evidence suggesting that depressed people evoke negative interpersonal interactions from others, I hypothesized that conversational partners of students with more past year depressive symptoms and who qualified for lifetime MDD would tend to engage in less interpersonal coordination.

CHAPTER II: METHOD

Method

Sample and Recruitment

The present study is a secondary data analysis of an existing sample of college students' text message communications and self-report survey data. Full details of study design and recruitment can be found elsewhere (Hussong et al., 2020). Briefly, as part of a larger study on harmonization techniques for pooling substance use data, participants completed two lab-based visits separated by 2 weeks during 2014-2015. Participants were recruited through e-mail invitations sent to 9,000 undergraduate students at UNC Chapel Hill. Invitees were randomly sampled from all enrolled students who were aged 18–23, with oversampling for males and African Americans given their underrepresentation in the student body (compared to the US population in that age bracket). To participate in the study, students had to report alcohol use in the past year. An additional 57 people contacted the study team directly asking to participate, resulting in a recruitment pool of 9,057. Of these, 17% completed the prescreen survey with 1,141 (75% of those screened before sample size targets were met) qualifying for participation.

The original study included two laboratory visits; a total of 854 students completed the first visit and 840 completed both visits. To be included in the current analysis, students had to successfully provide text message data in a second study that occurred immediately at the end of the second visit. Given a delayed start date for this protocol, 811 of the 840 participants in Visit 2 were invited to be in the text study. To be eligible for the text study, participants had to have an Android or iPhone with them (n = 780) and consent to participate (n = 531). Reasons for refusing consent included privacy concerns (19% of those invited to participate); time constraints (5%);

not being motivated by the incentive (<1%), not using SMS text messaging (<1%), primarily texting in a non-English language (<1%); and disinterest/no reason (5%).

One goal of the text study was to determine the feasibility of downloading 2 weeks of text data from students' personal phones. An advantage of this method over providing participants with study phones is that the text messages captured were not subject to nonreporting or self-censoring biases (e.g., changes in texting behavior because of being in a study). However, this method did require many adjustments in software platform as OS and other updates rolled out over the course of data collection. As a result, text data downloads were sometimes not successful, resulting in a 50.6% capture rate and 267 participants successfully contributing text data to the current analysis. On average, these participants sent 932 texts and received 1,294 texts over the 2-week study period (for a cumulative 569,172 texts sent and received over the study period).

The text sample – like the larger survey sample— was highly comparable to the undergraduate student body from which the sample was drawn on all demographic indicators, though more ethnically diverse (by design) and less evenly distributed across matriculation status. The text message sample comprised 267 college students (mean age = 19.87; 40.8% male; 56.82% White, 21.97% Black, 7.58% Asian, 0.38% Native American, 6.44% two or more races, and 7.58% Hispanic of any race); students in the text sample did not differ from the rest of the sample (without text data) on any of these demographic indices except that they were less likely to be male ($\chi^2(1) = 4.12$, $p = .046$) and Asian ($\chi^2(1) = 5.71$, $p = .02$). The text sample was also comparable to the rest of the sample on past year alcohol use frequency and quantity, and frequency of heavy alcohol use (Hussong et al., 2020).

Measures

Survey Measures

Participants filled out survey measures in both lab visits and contributed their past 2 weeks of text-message data at the second lab visit. Here, demographic variables and past-year depression symptoms were drawn from the first lab visit, while lifetime MDD was drawn from both lab visits. These measures are self-reported and only available for the study participant (henceforth, the 'target') and not for conversation partners (henceforth "partners").

Demographic covariates. Covariates included gender (male/female), race/ethnicity (dummy coded as White, Black, and Other race/ethnicity), and parental education computed as the highest of mother and father education (as a proxy for SES; response options included 1=less than high school, 2=high school graduate, 3=some college or technical school, 4=college graduate, 5=some graduate, medical or professional school, and 6=completed graduate, medical or professional school). These covariates were chosen because they often overlap with verbal and written speech style (Ireland & Pennebaker, 2010) and with depression (Brody et al., 2018) and could thus serve as potential confounds.

Current Depression. Past year depression symptoms were measured using the 13-item, unidimensional Short Mood and Feelings Questionnaire (SMFQ; Angold et al., 1995). Participants were provided with 13 "I statements" that reflected symptoms of depression (e.g., "I felt miserable or unhappy," "I found it hard to think or concentrate"). Participants responded using the original SMFQ response scale (0=not true, 1= sometimes, 2= true) to indicate if the item described how they have acted or felt in the past twelve months. The SMFQ has high internal consistency (alpha=.85) and is found to correlate moderately with the Diagnostic Interview Schedule for Children and the adult Clinical Interview Schedule-Revised Form

(Angold et al., 1995). Although three depressive symptoms in the DSM are not evaluated in the SMFQ (changes in sleeping patterns, changes in eating patterns, and suicidal ideation), the SMFQ is still found to have very high discriminant validity for Major Depressive Disorder in late adolescence (AUC= .90; Turner et al., 2014).

Due to the purpose of the parent study's design (on harmonization techniques for pooling substance use data), I used harmonized scores for the SMFQ (which was administered in two different versions randomly assigned within the sample); one version was the original scale and the second had half of the item stems altered for wording (not meaning). To illustrate: Half the sample received Test Form A, in which the original SMFQ asked how frequently each statement described them in the past year using a 3-point response scale ("not true," "sometimes," "true"). The other half of the sample received Test Form B, in which half of the item stems differed between forms (e.g., "I cried a lot" in Test Form A and "I had crying spells" in Test Form B) but with identical response scales. I harmonized these items using moderated nonlinear factor analysis (MNLFA; Bauer, 2017; Bauer & Hussong, 2009; Curran & Bauer, 2011) an iterative model-testing and scoring procedure (as described by Gottfredson et al., 2015) that takes into account potential differential item functioning across groups (in this case survey form; Cole & Hussong, 2020). In a similar (overlapping) sample, MNLFA yielded final scores which adjusted for differential item functioning and evidenced high internal consistency ($\alpha = 0.91$ in Test Form A; $\alpha = 0.92$ in Test Form B) and test–retest reliability ($\beta = 0.80$ in Test Form A; $\beta = 0.85$ in Test Form B; Cole & Hussong, 2020).

Harmonization in this Sample

Harmonization consists of freely estimating only items that are invariant (do not vary) by category—in this case by battery type. We expected that the items with the same wording across battery type would be invariant, and that in some other cases the variation in wording might also not alter responses and thus would be invariant. The sample used to harmonize scores was the entire sample that completed one or both surveys, not just those who contributed text messages n=851). This gives a larger pool to establish invariance of the item forms, since there do not appear to be systematic demographic differences between the text sample and the survey sample (Hussong et al., 2020).

First, it was examined whether Battery A and Battery B differed in the mean of the latent depression variable (mean impact) and in the variance of the latent depression variable (variance impact). Then, differences by battery in factor loading and item intercept of each of the 13 depression indicators were examined. Step 1 was aided by the R package *aMNLFA* (Cole et al., 2021) and *MplusAutomation* (Wiley & Hallquist, 2018). At Step 1, the threshold for "marginal" noninvariance (or Differential Item Functioning, DIF) was $p<.05$ for item loadings or intercepts and $p<.10$ for mean impact and variance impact. There were significant differences by battery type on the mean and variance of the depression latent variable and there were also differences by battery type in the factor loadings of five items: Factor loadings exhibited DIF on 3, 4, 5, 7, and 8 but were invariant on items 1, 2, 6, 9-13. The intercept was invariant on item 8, 11, and 13, but showed DIF in the other items.

In Step 2, all the terms that had at least "marginal" DIF at step 1 were included in a model simultaneously. Then the Benjamini Hochberg False Detection Rate (FDR) procedure with a 5% false detection rate was used to trim terms from the Step 2 model that were now invariant after accounting for FDR. The mean impact and variance impact were invariant at Step 2. Two intercepts, on items 8 and 10, had DIF in Step 2 in addition to those with DIF at Step 1. No additional item loadings showed DIF.

Step 3 involved running a model freely estimating differences by battery type only on the items that had DIF at the FDR trimming in Step 2. Thus, the mean and variance impact were constrained by battery type. However, model identification issues emerged at Step 3. To correct the error at Step 3, the mean and variance impact were again freely estimated (allowed to vary across battery) in the model. When this was done, the model was identified, and mean impact again emerged (p = .012). Thus, the final model included mean (but not variance) impact on the latent depression variable alongside differential item functioning (DIF) on both loading and intercepts for four items (3,4,5,7), DIF on the intercept only for four items (1,2,6,9), and DIF on the loading only for 1 item (8). Conversely, in the final model, four items are fully invariant, four items have an invariant loading only, one item has an invariant intercept only, and the remaining four items were fully noninvariant (DIF in both loading and intercept). Although it was somewhat surprising that only two out of six items that had the same wording across battery were fully invariant (as were two of the five items that differed in wording), this was consistent with previous experiences with harmonization in this dataset (Veronica Cole, personal communication). A possible explanation is that items with the same wording may have been impacted by differences in previous items (Schwarz, 1999). By testing for any observed impact and DIF of items on battery A and B, we created factor scores adjusted for these systematic differences and measurement artifacts that we then used as a cohesive measure of depressive symptoms.

Table 1. Harmonization of the SMFQ via MNLFA

Term	Battery Type		DIF/Invariance
	Form A	Form B	
DEP01	I felt miserable or unhappy	I felt miserable or unhappy	Intercept DIF
DEP02	I didn't enjoy anything at all	I didn't enjoy anything at all	Intercept DIF
DEP03	I felt so tired I just sat around and did nothing	I felt so tired I just sat around and did nothing	Intercept and Loading DIF
DEP04	I was very restless	I felt so fidgety or restless	Intercept and Loading DIF
DEP05	I felt I was no good anymore	I felt I was no good anymore	Intercept and Loading DIF
DEP06	I cried a lot	I had crying spells	Intercept DIF
DEP07	I found it hard to think properly or concentrate	I found it hard to think properly or concentrate	Intercept and Loading DIF
DEP08	I hated myself	I didn't like myself	Loading DIF
DEP09	I was a bad person	I felt bad about myself	Intercept DIF
DEP10	I felt lonely	I felt lonely	Fully invariant
DEP11	I thought nobody really loved me	I thought nobody really loved me	Fully invariant
DEP12	I thought I could never be as good as other people	I did not feel like I was as good as other people	Fully invariant
DEP13	I did everything wrong	I thought my life had been a failure	Fully invariant
Depression Latent Variable Mean			Impact
Depression Latent Variable Variance			No Impact

Note. Items that are shaded in gray are those that vary slightly in wording (but not in meaning) by battery type.

Lifetime Depression. A lifetime history of Major Depressive Disorder was also assessed using the criteria set forth by DSM IV and DSM-5 (depression criteria did not change). Our lifetime MDD measure includes those who met criteria for depression in the past year and those who met criteria at a prior time in their life. At each lab visit, part of the sample (randomly selected) received a measure based the SCID (First et al., 2015) assessment of MDD, while others received a measure based on the CIDI-SF (Kessler et al., 1998). Unfortunately, there was a survey coding error which rendered the CIDI-SF unusable. Thus, here, SCID MDD diagnosis from both lab visits was utilized; if the participant qualified for a diagnosis at either visit, they were be coded as having (1), versus not having (0) a lifetime history of MDD. Of the 192 participants who completed the SCID interview at either lab visit, 26 (13.5%) qualified for lifetime MDD and 11 (5.7%) qualified for past year MDD. Thus, 15 people (7.8%) qualified for lifetime but not recent MDD—a remitted group. Because 75 people's MDD scores are missing at random, given that their random assignment to complete either the CIDI-SF or SCID led to missingness, we used FIML estimation to handle this missing completely at random (MCAR) data and thus retained the complete sample for analysis.

Relationship Type. Participants were asked to provide the phone numbers of a mother, father, romantic partner, and three best friends if applicable. For those identified, text message conversations could be linked to these roles: 96.9% of targets identified a mother as a texting partner, 88.6% identified a father, 50.6% identified a romantic partner, and 100% identified at least one friend. The relationship identity of other texting partners was not assessed (though they are flagged with unique conversation identifiers to enable analysis of each conversation separately). That is, I know how many "other" conversations our target participants had, but I do not know with whom they were interacting (i.e., they could be friends, relatives, classmates, coworkers, or any other person).

Text-Analysis Measures

Language Style Matching. Interpersonal coordination of language style (language style matching, interchangeable with the term linguistic style matching) is measured here using written text message communication content. Language Style Matching has been operationalized in multiple metrics, and one way they differ is whether they compute matching at the overall conversation level or on a statement-to-statement level. I selected a measure developed by Müller-Frommeyer and colleagues (2019) called reciprocal Language Style Matching (rLSM) that captures statement-to-statement matching, permits distinguishing how much each speaker is matching, does not confound matching with overall word count, and is simple to compute. Most research on interpersonal coordination in language thus far has used different measures (e.g., statement to statement correlation or proportion of matching at the overall conversation level) but for my purposes, reciprocity and sensitivity to relative frequency were very important, so rLSM was the most informative measure of interpersonal coordination in language style.

Several data preparation steps preceded computing rLSM (see Table 2 for a summary of the number of targets, dyads, and texts/talk turns at each step of data preparation). To aid with data cleaning and visualization, and later with data analysis, I used the R packages dplyr (Wickham et al., 2021), ggplot2 (Wickham, 2016), and psych (Revelle, 2021).

Data Cleaning Approach. Multiple approaches exist for addressing data cleaning in natural and text-based language. A common approach is to leave natural language unaltered and allow irregularities (such as misspellings or special characters) to “wash out” in the very large sample (Tausczik & Pennebaker, 2010). Another approach is to try to correct these irregularities, at least in part, with computationally intense dictionary-based methods or even machine-learning algorithms. Here, I took the common approach of leaving possible misspellings, non-standard English, and text lingo unaltered, which resulted in words that were not recognized by the word counting software (LIWC). This approach was chosen due to pragmatics and because the focus of the present study is function words (which are usually short and perhaps less subject to misspellings), although I recognize that there are examples of common text lingo that include function words (e.g., Hbu- how about you?, Wyd- what are you doing?) that were not captured.

However, there was one data cleaning process that we decided a-priori would was important given the nature of our text message data. Some of the text messages in the original sample were not in English and some not in the Roman alphabet—undetectable by our word counting software and by our measure of language style matching which use *English* language function words. Thus, computing rLSM in conversations that are most non-English yields extremely low or zero scores—outliers—that are not meaningful but could interfere with accurate model estimation. Thus, the following steps were taken to address non-English text messaging and identify dyads that mostly communicated in languages other than English.

Step 1: Language Detection. We made the decision to exclude *dyads* with a preponderance of non-English text messaging rather than to exclude individual text messages in non-English language. This decision acknowledges that rLSM is computed on a turn-by-turn basis within dyads (as described in greater detail later), so excluding text messages within adjacent turns would disrupt the succession of the natural conversation and meaning of rLSM.

Detecting the language of short messages (such as texts or Tweets) in a sample with multiple languages continues to be a challenging area of natural language processing (Hughes et al., 2006; Vo & Khoury, 2020). We used language detection R packages cldr2 and cldr3 (Ooms, 2020, 2021) which replicate the Google language detection algorithms for the R open-source platform (R Core Team, 2021). Each has strengths and weaknesses, and I used them in combination as recommended by package documentation (https://cran.r-project.org/web/packages/cld3/cld3.pdf). Steps of the process are expounded below.

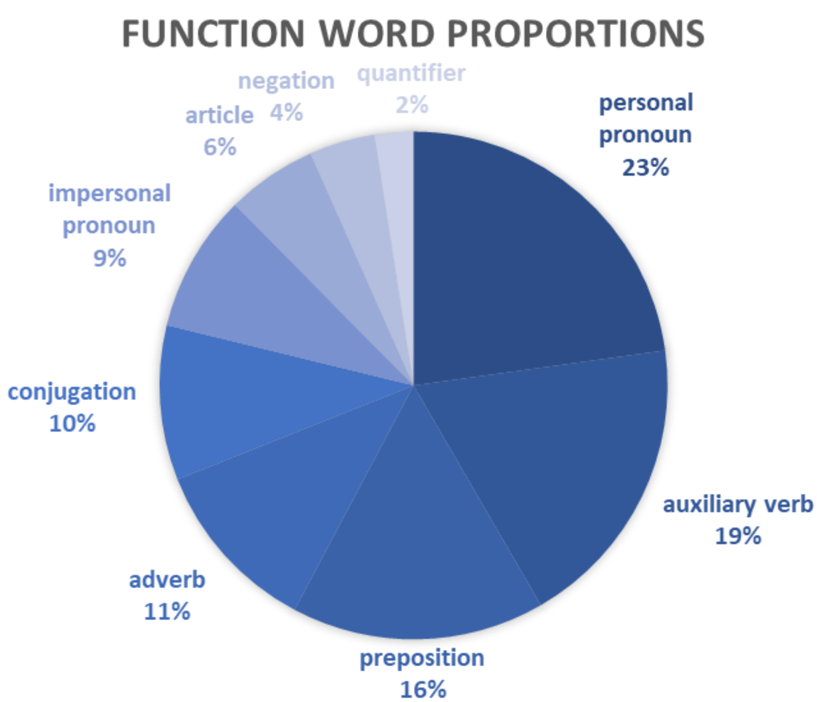
a. Upon running the cldr2 and cldr3 on the entire text message sample, each language detector classified each text message as a specific language (e.g., English, Spanish, Portuguese, etc.) or unknown language (*NA*). Most of our texts were classified as English by both detectors (N = 308,425; 54.19%) and upon visual inspection these messages appeared to be all or almost all in English. Another portion was classified as English by one detector but as a specific non-English (N = 36,800; 6.47%) or unknown (N= 80,757; 14.19%) language by the other detector. Upon visual inspection these messages appeared to be all or almost all in English. Of the texts that were classified as a non-English language by one detector and NA by the other (N = 89,924; 15.80%), most appeared to be English text lingo or special characters, and of the ones classified as NA as by both detectors (51,644; 9.07%) most appeared to be short (one- to three-word) texts in English. The remaining small number of texts were classified as a non-English language by both detectors—some were classified as the same non-English language (N=557; .10%) and others two different non-English languages (N = 1065; .19%)—and on visual inspection they were mostly non-English. Exceptions were a few instances of English text lingo and some words that are not in any language such as names and email addresses.

b. All dyads that had at least one text classified as a non-English language by both detectors (727 dyads from 220 participants, 263,646 texts) were examined for the proportion of texts classified as non-English. From visual inspection, in dyads with 25% or more texts classified as non-English, most texts were not in English, and thus 25% was used as the cutoff for dropping the dyad. With this rule, 44 dyads from 37 participants constituting 632 texts were dropped. Thus, at the end of language detection 568,540 texts from 267 people and 9,895 dyads remained for analysis.

Step 2: Collapsing Texts into Talk Turns. When texting, sometimes people send multiple messages in succession before their conversation partner responds. Language Style Matching is computed between a statement from one speaker and the next statement from the other speaker. Rather than using the last text in a succession of texts and disregarding the rest, I chose to collapse successive texts by the same speakers (summing the word counts and function word category counts to compute a talk turn total). All the talk turns for each dyad are considered a continuous conversation (e.g., not subdivided into days) as we think this best reflects that the asynchronous nature of text messages allows a single conversation to carry on across days. The dataset includes a total of 329,622 talk turns within a total of 9,895 dyads among our 267 target participants.

Step 3: Computing Word Counts in Language Categories. I used the Linguistic Inquiry and Word Count (LIWC, Pennebaker et al., 2001, 2007) program to quantify the number of words in each text message that belong to each function word category as specified by the LIWC dictionary. LIWC has 9 function word categories that I will use here: personal pronouns (e.g., I, you, we), impersonal pronouns (e.g., it, it's, those), auxiliary verbs (e.g., am, might, would), articles (e.g., a, an, the), common adverbs (e.g., very, really, quickly), prepositions (e.g., to, with, above), negations (e.g., no, not, never), conjunctions (e.g., for, and, but), and quantifiers (e.g., few, many, much). These are the same categories used by most LSM studies in English, although function categories available in other languages differ (e.g. Müller-Frommeyer et al., 2019) and some LSM studies in English have chosen to analyze 11 categories, separating among personal pronouns (1st, 2nd, and 3rd person). In summary, we used LIWC to extract a count of each function word category and the total word count for every text message in the sample. The dataset at this point included a total of 2,853,143 function words (comprised of the categories shown in Figure 2) within a total word count of 4,529,497 in the entire text sample (N=267 college students). The function words remaining in the analysis sample are depicted in Figure 2.

Figure 2. Function Words Comprising rLSM



Note. The dataset includes a total of 2,707,299 function words (approximately 64% of the total word count of 4,256,671, although this is a slight overestimate as some words are counted as several categories by LIWC) in the entire text sample (N=267 targets).

Step 4: Computing rLSM. The fourth and final step was to compute the desired measure of reciprocal language style matching—an rLSM value for each target and partner. This was done in several sub-steps.

1) First, I computed rLSM scores for every function word category in every talk-turn (other than the first talk turn per dyad, as the first speaker has no previous talk turn to match) for each texting partner. At the talk-turn level (the basic unit of rLSM) rLSM is calculated via the equations below, representing the matching of function words in consecutive statements from one texting partner to the other, as a proportion of the total statements by both speakers. Speaker A is simply the first in a dyad to speak, and speaker B is the second. Equation 1, a measure of speaker A's reciprocal language style matching, quantifies how much the *i* +1 statement of speaker (A) matches the *i*th statement of the other speaker (B). Equation 2, a measure of speaker B's reciprocal language style matching, quantifies how much the *i*th statement of speaker B matches the *i*th statement of speaker A. Matching is the absolute difference in the proportion of words in a given LIWC category (C; here, our Categories include the nine function word categories personal pronouns, impersonal pronouns, auxiliary verbs, articles, common adverbs, prepositions, negations, conjunctions, and quantifiers) by each speaker. For example, for pronouns (P) in speaker A's first statement, I can write the term $C_A^{S=i}$ as $P_A^{S=1}$. To prevent an undefined value when there are zero instances of the category, 0.0001 is added to the denominator (following the practice set by Ireland & Pennebaker (2010) when measuring LSM via a proportion).

$$rLSM_A(C) = 1 - \frac{\left|C_B^{S=i} - C_A^{S=i+1}\right|}{C_B^{S=i} + C_A^{S=1+1} + 0.0001} \qquad \text{Equation 1}$$

$$rLSM_B(C) = 1 - \frac{|C_A^{S=i} - C_B^{S=i}|}{C_A^{S=i} + C_B^{S=i} + 0.0001} \qquad \text{Equation 2}$$

2) The next step was to compute an average rLSM from all the function word categories (Müller-Frommeyer et al., 2019; Niederhoffer & Pennebaker, 2002) for each talk turn. Consistent with past research (Müller-Frommeyer et al., 2019) each category is weighted equally, even though frequencies of the function words are widely different, as shown in Figure 2. For each of the 329,622 talk turns, there is now one rLSM score (representing the average proportion of matching for function words in that turn).
3) Third, I computed an unweighted average of rLSM scores for each participant (across all that person's talk turns, separately for sent and received messages). This yields two rLSM scores per participant, which capture the individual (person) differences in rLSM in the messages they send (target rLSM) and receive (partner rLSM) over the two-week study period. Computing an unweighted score means that those interactors with whom a target participant texts more will contribute more heavily to their rLSM score than those interactors with whom they text less frequently. For example, if a participant sent twice as many talk turns to their romantic partner than to their mother, then how much they matched their romantic partner will influence their rLSM score more than how much they matched their mother. This is in accordance with our interest in individual differences, aside from relationship context; individual-level rLSM scores are of primary interest for this investigation, as we hypothesize that a target student's depression will relate to their engagement in rLSM.
4) Finally, rLSM values were scaled to be between 0 and 100 (rather than 0 to 1) to facilitate interpretation of results (i.e., a 1 unit increase in rLSM now represents a 1% increase in linguistic style matching).

Step 5: Excluding dyads with few rLSM values. Some text message dyads did not offer a meaningful sample of rLSM values because they were too short, one-sided, or mostly non-verbal. For example, some dyads exchanged only a name and email address, others were automated reminders, and others were mostly emojis or pictures that cannot be captured with the current system of language style matching. Thus, these rLSM values were not valid for our purpose.

As a cutoff, we elected to keep conversations with two or more rLSM values for several reasons. By definition, a conversation with two rLSM values must have at least three talk turns and at least three text messages with a nonzero word count. 1,119 dyads from 246 people exchanged zero words—meaning they only exchanged emojis, pictures, or special characters—in the two-week time frame these messages were collected. We cannot capture coordination in visual media with our rLSM measure. Another 3,336 dyads exchanged one or two talk turns, and from qualitative observation, these talk turns had little substance and often consisted of single words. Requiring at least two rLSM values increases the likelihood that measures of reciprocity capture verbal and more substantive conversation that offers an opportunity for matching. In all, 3,527 dyads (who exchanged 4,616 talk turns) did not meet the cutoff of having two or more rLSM values and were thus excluded from analysis, leaving 325,006 talk turns (6368 dyads, 267 targets).

Step 8: Examining Dyad Members with no rLSM. After computing rLSM values and excluding dyads with less than two rLSM values, there remained 60 dyads in which all valid rLSM values were from a single member of the dyad. This is possible when one member (e.g., Person A) uses a function word but the other member (e.g., Person B) does not use any function words in response, and thus never provides an opportunity to match. In this example, Person A's average rLSM with Person B would be NA, whereas Person B's average rLSM with Person A would be a nonzero value. Since it is unusual to use no function words in a substantive conversation, we flagged these 60 dyads for closer examination.

Table 2. Data Preparation

Process	N	Dyads	Texts/Talk Turns
Original	267	9939	569172 texts
Language Detection	267	-44 = 9895	- 632 = 568540 texts
Talk Turns	267	9895	329622 turns
2+ rLSM values	267	-3527 = 6368	- 4616 = 325006 turns
Substantive	266	-16	- 300 turns
Primary Model	**266**	**6352**	**324706 turns**

Note. This table depicts data cleaning steps, along with the composition of targets, dyads, and texts/talk turns at each step, leading up to the Primary Model dataset used for planned analyses.

Upon inspection of the 60 dyads flagged as one-sided, many were short (4 talk turns) but meaningful exchanges between humans. However, 16 dyads (comprised of 300 talk turns total) were non-substantive in that they were interactions with an automated system, including a bus line, a banking system, a class poll, or a ride service. One of these was a non-English conversation (that had passed language detection because of a few English words, including two function words, in an overall brief conversation). This conversation was the only one for that target participant that had remained after earlier exclusion steps and was dropped at this step (therefore the number of targets and partners were reduced to 266). After dropping non-substantive dyads, the final dataset used for the primary analysis was composed of 266 target participants, 6352 dyads, and 324,706 talk turns.

CHAPTER III: ANALYSES

Analyses

Preliminary (Descriptive) Analyses

Text Descriptive Statistics

Word counts in the final set of dyads ranges from 6 to 29,375 (*M* = 670.13, *SD* = 1,773.45, Median = 200) words exchanged per dyad. The word count per Target within a dyad ranged from 1 to 18,096 (*M* = 365.92, *SD* = 941.69, Median = 107). The word count per Partner within a dyad ranged from 1 to 16,386 (*M* = 304.21, *SD* = 886.51, Median = 84).

Individual Differences

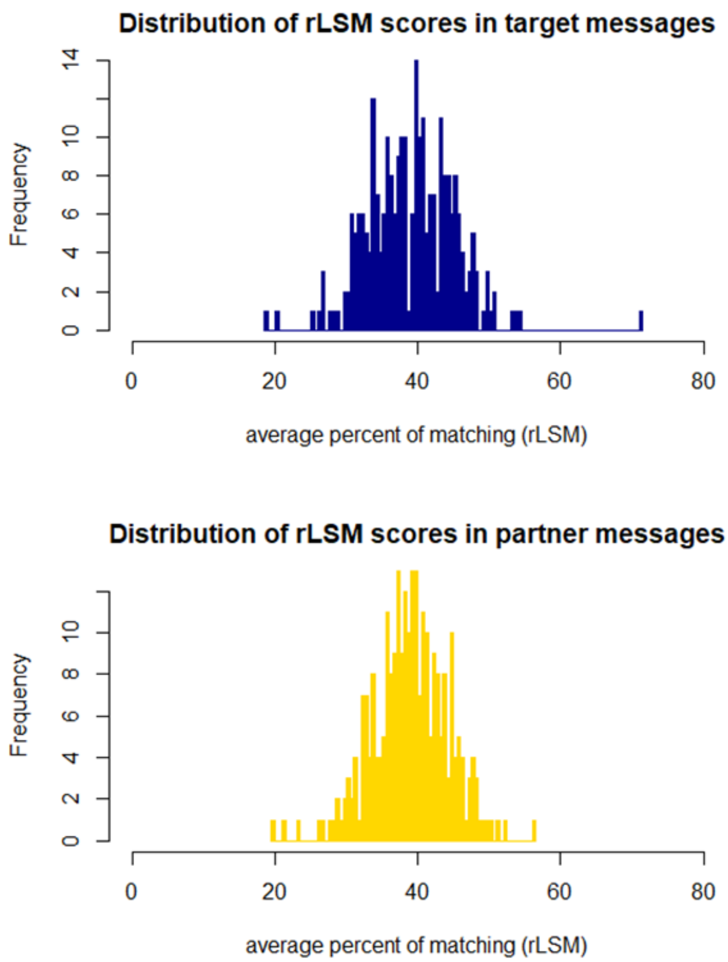
Descriptive statistics were computed for individual differences (between the 266 targets) on computed rLSM scores in sent (from the target) and received (to the target) text message talk turns and are shown in Table 3. Mean rLSM values are close to those found in a previous study of rLSM conducted in German—between 0.3 and 0.4 matching on a turn-by-turn basis (Müller-Frommeyer et al., 2019). There is interindividual variability among both targets and partners that follows an approximately normal distribution (as shown in Figure 3).

Table 3. Descriptive Statistics of Reciprocal Language Style Matching by Individual

Role	N	*M*	*SD*	min	max	skew	kurtosis
Target	266	39.06	6.17	18.84	71.46	0.36	2.38
Partner	266	38.91	5.35	19.56	56.40	-0.20	0.74

Note. This table depicts the average level of matching on function words on a turn-by-turn basis (reciprocal language style matching; rLSM) in targets (N = 266) and their conversation partners.

Figure 3. Interindividual Variability rLSM Scores in Sent and Received Messages



Note. This figure depicts the average level of matching on function words on a turn-by-turn basis (reciprocal language style matching; rLSM) in targets (N = 266) and their conversation partners; see Table 2). The distributions are approximately normally distributed.

Relationship Type Differences

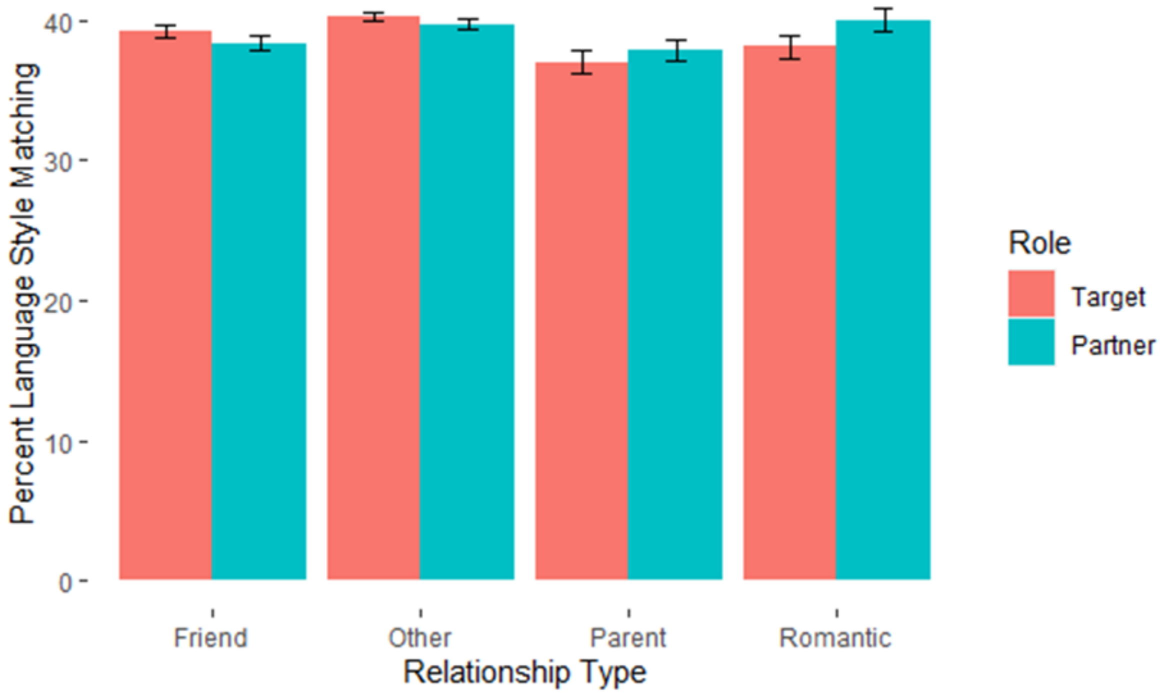
An initial descriptive step was to examine the variability in how much people engage in interpersonal coordination across their different relationship types. Descriptive analyses are shown in Table 4 and Figure 4. As shown, interpersonal coordination by both targets and partners was lower (slight but statistically significant difference) in close relationships (parent, romantic, and friend) than in other relationships. This was somewhat surprising, given that we suspected that people in closer relationships would show more interpersonal coordination in text messages. Given that differences among relationships were slight, we chose to focus on individual difference (between people) aggregating across all relationship types in this analysis.

Table 4. Descriptive Statistics for rLSM by Relationship Type

Relationship Type	Target			Partner		
	n	*M*	*SD*	*n*	*M*	*SD*
Parents	227	37.88	11.88	227	37.02	11.57
Romantic	121	40.01	8.64	121	38.10	8.94
Friends	261	38.37	7.61	261	39.24	7.47
Other	263	39.72	6.55	263	40.24	5.25

Note. Talk turns in the primary dataset come from conversations with parents (18,858 talk turns, 5.8%), romantic partners (71,468, 22.0%), three closest friends (84,766, 26.1%), and other relationships 149,614 (46.1%). This table displays a preliminary analysis to detect differences in average levels of language style matching across relationship types (see also Figure 4). A small but significant difference was found between “close” relationships (romantic, parent, and friend) and other relationships in a surprising direction—other relationships coordinated more.

Figure 4. Reciprocal Language Style Matching by Relationship Type



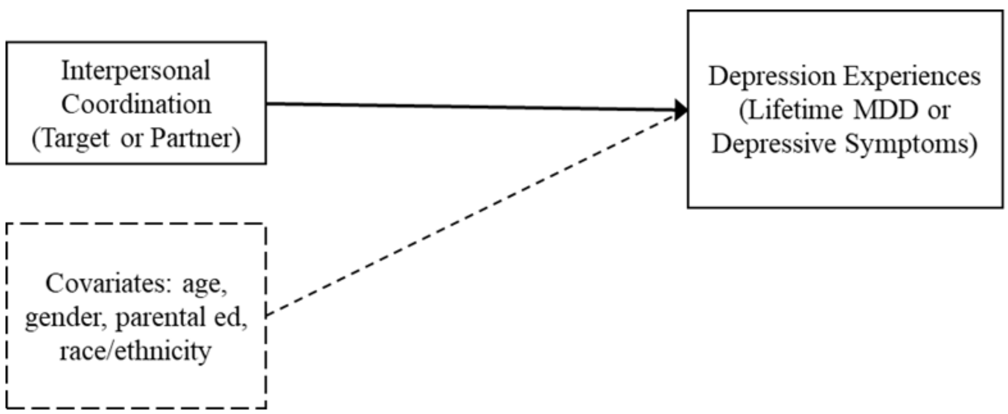
Note: This table displays a preliminary analysis to detect differences in average levels of language style matching across relationship types (see also Table 4). A small but significant difference was found between "close" relationships (romantic, parent, and friend) and other relationships in a surprising direction—other relationships coordinated more.

Primary Analyses

The primary question of interest is whether interpersonal coordination (as measured by rLSM) is associated with more depression experiences (past-year depressive symptoms and lifetime MDD). I expected that people who coordinate less or whose texting partners coordinate less would be more likely to have more depression experiences. To test this, I ran four separate models testing how coordination (target or partner) was associated with depression experiences of the target (depressive symptoms or lifetime MDD). More specifically, these Structural Equation Models (SEM; see Figure 5) tested the association between 1) target coordination and depressive symptoms, 2) target coordination and lifetime MDD, 3) partner coordination and depressive symptoms, and 4) partner coordination and lifetime MDD, alongside demographic covariates: gender, age, parental education (as a proxy for SES), and dummy coded race/ethnicity. I conducted analyses in MPlus (8.1, Muthén & Muthén, 1998-2017) using MLR, which examines the incremental relationships of each of the predictor variables over and above salient covariates and which yields regression estimates, confidence intervals, and effect size measures for both depression symptoms (a continuous outcome) and lifetime MDD (a binary outcome). Missing data was handled using full information maximum likelihood estimation (FIML), an efficient method for handling missing data in structural equation models that reduces biases present in other methods (Enders & Bandalos, 2001). FIML assumes that missing data are at least Missing at Random (MAR; Muthén et al., 1987) and we are confident that our measure of lifetime MDD is Missing Completely at Random (MCAR) since scores are missing for only one of two *randomly assigned* conditions.

Originally, I planned to test all study hypotheses in a single, parsimonious model that included coordination from target and partner and both depression experience outcomes. However, this complex model (which included both a sparse binary and a continuous endogenous variable alongside correlated predictors and missing data) yielded errors (model identification and a non-positive definite covariance matrix). We resolved these issues by estimating separate models for each predictor-outcome pair. The only downside of this method compared to a single structural equation model is that it does not yield estimates of the relative strength of prediction of target rLSM over and above partner rLSM (and vice versa), but (as shown in the Results below), there were few significant associations between depression experiences and partner rLSM and thus this is of less concern. Thus, we ran four Structural Equation Models (SEM; see Figure 5). Models were saturated, so fit indices are not reported. Racial-ethnic groups were dummy coded as Black, White, and other (reference) race/ethnicity. The percentage of people with lifetime depression was 9.8% (N = 26) out of the 266 participants.

Figure 5. Primary Model



Note. We examined whether interpersonal coordination (target or partner) predicted depression experiences (depressive symptoms and lifetime MDD), alongside demographic covariates: gender, age, parental education (as a proxy for SES), and dummy coded race/ethnicity in four Structural Equation Models (SEM).

CHAPTER IV: RESULTS

Results

Results of the primary and sensitivity analyses are summarized in Tables 5-8.

Primary Analyses

Table 5. Interpersonal Coordination and Depression in Primary Analyses

Predictor	Depression Experiences							
	Lifetime MDD				Past Year Depressive Symptoms			
	b (SE)	*p*	*OR*	CI (*b*)	*b* (SE)	*p*	*β*	CI (*b*)
Target rLSM	.037 (.046)	.419	1.038	-.053, .128	.008 (.010)	.426	.048	-.012, .028
Gender	-.983 (.504)	.051	.374	-1.97, .004	-.103 (.130)	.428	-.049	-.359, .152
SES	-.155 (.157)	.324	.856	-.464, .153	.012 (.047)	.801	.016	-.081, .105
Black	-.874 (.721)	.225	.417	-2.287, .538	-.004 (.188)	.981	-.002	-.372, .364
White	-.439 (.601)	.465	.645	-1.616, .739	-.113 (.147)	.442	-.053	-.402, .175
Age	.157 (.168)	.350	1.17	-.172, .487	.031 (.044)	.477	.042	-.055, .117
Partner rLSM	.068 (.049)	.162	1.07	-.027, .163	<.001 (.012)	.977	.002	-.022, .023
Gender	**-1.036 (.517)**	**.045**	**.355**	**-2.05, -.022**	-.112 (.131)	.395	-.053	-.369, .145
SES	-.168 (.163)	.303	.845	-.488, .152	.011 (.047)	.813	.015	-.082, .104
Black	-.840 (.696)	.228	.432	-2.204, .525	-.013 (.188)	.945	-.005	-.382, .356
White	-.459 (.602)	.446	.632	-1.64, .721	-.097 (.148)	.512	-.045	-.387, .193
Age	.123 (.172)	.476	1.131	-.215, .460	.038 (.045)	.398	.051	-.050, .125

Note. $N = 266$ for both targets and partners. Raw coefficients (*b)* and standard errors (*SE*) reported alongside standardized regression coefficients *(β),* odds ratios (*OR*), and the 95% confidence intervals (CI) for *b*. Significant values ($p<.05$) are bolded.

Contrary to hypotheses, the interpersonal coordination of *targets* was not significantly associated with their depression experiences as indexed by either past year depressive symptoms or lifetime MDD (see Table 5). Interpersonal coordination by their conversation *partners* was also not significantly associated with depression experiences (see Table 5).

Sensitivity Analysis- Romantic Relationships

Table 6. Interpersonal Coordination and Depression in Romantic Relationships

Predictor	Depression Experiences							
	Lifetime MDD				Past Year Depressive Symptoms			
	b (SE)	*p*	*OR*	CI (*b*)	*b* (SE)	*p*	*β*	CI (*b*)
Target rLSM	.005 (.049)	.917	1.005	-.091, .101	-.002 (.012)	.879	-.014	-.025, .022
Gender	-.800 (.600)	.183	.449	-1.977, .377	-.066 (.219)	.763	-.029	-.495, .363
SES	.003 (.206)	.986	1.003	-.400, .407	.022 (.072)	.765	.027	-.120, .163
Black	-1.662 (.935)	.075	.190	-3.495, .170	-.085 (.292)	.772	-.031	-.656, .487
White	-.861 (.750)	.250	.423	-2.331, .608	-.121 (.229)	.598	-.052	-.570, .329
Age	.049 (.197)	.804	1.05	-.337, .434	.019 (.068)	.776	.024	-.113, .152
Partner rLSM	.053 (.036)	.142	1.055	-.018, .124	-.010, .011	.325	.083	-.031, .010
Gender	-.847 (.601)	.159	.429	-2.025, .332	-.061, .218	.779	-.027	-.488, .366
SES	<.001 (.218)	.999	1.000	-.427, .428	.029, .073	.694	.036	-.115, .172
Black	-1.596 (.933)	.087	.203	-3.425, .234	-.095, .293	.746	-.035	-.670, .480
White	-.924 (.749)	.217	.397	-2.391, .544	-.101, .239	.674	-.043	-.569, .368
Age	-.011 (.195)	.955	.989	-.394, .372	.027, .067	.685	.034	-.104, .158

Note. $N = 121$ for both targets and partners. Raw coefficients (*b)* and standard errors (SE) reported alongside standardized regression coefficients *(β),* odds ratios (*OR*), and the 95% confidence intervals (CI) for *b*. Significant values ($p<.05$) are bolded.

To explore the possibility that the hypothesized associations between interpersonal coordination and depression experiences only emerge in certain types of relationships (i.e., romantic relationships that have characterized many of the study samples in prior interpersonal coordination research), I conducted a sensitivity analysis running the same four SEM models as in the primary analysis in the conversations of romantic partners only. Selecting only romantic relationship dyads left 121 targets (out of 266; dropping 145), 121 dyads (out of 6352; dropping 6231), and 71,460 talk turns (out of 324,706; dropping 253,238). As in the primary analysis, the interpersonal coordination by *targets* in their text messages with their romantic partners were not significantly correlated with their depression experiences (see Table 6). Interpersonal coordination by *partners* also did not predict depression experiences.

Sensitivity Analysis- Standard English

To explore the possibility that features of this large and varied text message dataset may be clouding our ability to detect hypothesized associations, a second sensitivity analysis tested study hypotheses within the subset of text messages that used more standard English. Text messages that were classified as English by both language detectors appeared to be composed of more complete sentences with less text lingo. This type of language is more like spoken language and other types of written language (e.g., email) where linguistic style matching has been examined previously. Additionally, we suspected that this subset of text messages would be more likely to include function words that were written out fully, and thus detected and correctly classified as function words by LIWC. In "text lingo," many function words are embedded in abbreviations or alternate spellings such as these: "wby" (what 'bout you?), "hby" (how 'bout you?), "np" (no problem), "tty" (talk to you), "idk" (I don't know), "annnd" (and), "meeeee" (me), "ur" (your), "gimme" (give me), "gonna" (going to) and even idiosyncratic ones like "water" (what are). Thus, we isolated dyads with at least 50% of text messages that were classified as English by both detectors, leaving 263 targets (out of 266; 3 dropped), 4,773 dyads (out of 6,352; 1,579 dropped) and 207,942 talk turns (out of 324,706; 116,607 dropped).When we attempted a more stringent cutoff of 75% or more, only 23,277 talk turns would have remained, and 301,272 would have been dropped, which we saw as insufficient for analysis.

Like the primary dataset, in this subset that we call "standard English," function words made up most (64.5%) of the word count, and subcategories of function words were comparable. Word count in standard English dyads ranged from 11 to 29,375 (*M* = 637.51, *SD* = 1,669.64, Median = 208)—also about the same as the primary dataset. As seen in Table 7, talk turns in the standard English dataset come from conversations with parents (15,180, talk turns, 7.3%), romantic partners (37,828, 18.2%), three closest friends (53,102, 25.5%), and other relationships 101,878 (49.0%). The distribution of relationship types differed in messages from the primary sample that were included in the standard English sample compared to those that were excluded ($\chi^2(3) = 7171.4$, p = <.001). All post-hoc comparisons were significant (p<.001). This means that the primary sample had a higher proportion of conversations between romantic partners and close friends (and lower proportion of parents and others) compared to the standard English sample.

Table 7. Relationship Type Distributions in Standard English Subsample

Relationship Type	Primary Sample		Standard English		Non-Standard English	
	n	Talk turns	*n*	Talk turns	*n*	Talk turns
Parent	227	18,858	199	15,180	28	3,678
Romantic	121	71,468	80	37,828	41	33,640
Friend	261	84,766	226	53,102	35	31,664
Other	263	149,614	260	101,832	3	47,782

Table 8. Interpersonal Coordination and Depression in Standard English Model

Predictor	Depression Experiences							
	Lifetime MDD				Past Year Depressive Symptoms			
	b (SE)	*p*	*OR*	CI (*b*)	*b* (SE)	*p*	*β*	CI (*b*)
Target rLSM	**.079 (.038)**	**.040**	**1.082**	**.004, .154**	**.024 (.011)**	**.027**	**.127**	**.003, .045**
Gender	-1.095 (.559)	.050	.335	-2.191, .001	-.102 (.130)	.434	-.048	-.356, .153
SES	-.138 (.163)	.398	.871	-.458, .182	.017 (.047)	.727	.022	-.076, .109
Black	-.847 (.743)	.254	.429	-2.303, .609	.011 (.183)	.953	.004	-.348, .370
White	-.514 (.608)	.398	.598	-1.705, .678	-.162 (.142)	.256	-.076	-.441, .117
Age	.159 (.173)	.358	1.173	-.180, .499	.026 (.043)	.545	.035	-.058, .110
Partner rLSM	.027 (.041)	.514	1.027	-.054, .107	-.001 (.012)	.927	-.005	-.024, .022
Gender	**-1.036 (.525)**	**.049**	**.355**	**-2.066, -.007**	-.110 (.132)	.404	-.052	-.369, .149
SES	-.166 (.159)	.298	.847	-.478, .146	.009 (.049)	.859	.011	-.086, .104
Black	-.909 (.704)	.197	.403	-2.289, .472	-.013 (.188)	.946	-.005	-.382, .356
White	-.393 (.596)	.510	.675	-1.56, .775	-.110 (.149)	.459	-.052	-.402, .182
Age	.173 (.165)	.295	1.189	-.151, .497	.036 (.044)	.406	.049	-.049, .122

Note. *N* = 263 for both targets and partners. Raw coefficients (*b)* and standard errors (SE) reported alongside standardized regression coefficients *(β),* odds ratios (*OR*), and the 95% confidence intervals (CI) for *b*. Significant values (*p*<.05) are bolded

As seen in Table 8, and in contrast to the primary and romantic relationship samples, in the standard English sample there was a statistically significant association between interpersonal coordination of targets and depression experiences (both lifetime MDD and depressive symptoms), such that those students who evidenced more interpersonal coordination in their text messages were more likely to qualify for lifetime MDD and reported significantly more past year symptoms of depression. The size of these associations was non-trivial: For every 1 standard deviation unit increase in target rLSM, depressive symptoms increased by an estimated .127 standard deviations (CI .009, .246). For every 1 standard deviation unit increase in target rLSM, the likelihood of qualifying for lifetime MDD was estimated at 8.2% greater, with a confidence interval ranging from .4% greater to 16.7% greater (*OR*(SE)= 1.082 (.042), CI 1.004, 1.167).

However, like the primary and romantic relationship models, *partner* rLSM was not significantly associated with depression experiences.

CHAPTER V: DISCUSSION

Discussion

Interpersonal ineffectiveness has been widely implicated as a correlate of depression, and a varied body of research suggests linkages between interpersonal coordination specifically and depressive experiences. Fewer studies, however, have examined coordination of language style with depression, and no previous study had examined whether this association emerges in one of the most common modes of communication among young people: text messages. This study used a recently-developed approach to calculating LSM (rLSM; Müller-Frommeyer et al., 2019) in a large sample of naturalistic text messages exhanged by college students over two weeks to examine whether depressive experiences in the target college student participants were related to their own and their partners' engagement in langauge style matching. In the primary sample of 324,706 talk turns, we did not see evidence to support the hypothesized associations, though in a restricted sample of 207,942 talk turns sent and received in more standard English (characterized by fewer abbreviations and text lingo and more use of full sentences) we saw evidence that those college students with more depression experiences tended to have text message conversations characterized by *more* (not less, as hypothesized) interpersonal coordiantion of language style. Possible explanations for the emergence of this somewhat counterintuitive pattern in only the standard English subsample are explored below.

One reason that studies sometimes yield null results is that they were not adequately powered to uncover an effect, even if there was indeed an effect to be uncovered. The present study employed an existing sample 267 college students, which is within the typical sample size range of studies in the social/behavioral sciences. Rather than conduct a post hoc power analysis (the limitations of which have been outlines in detail elsewhere (Lakens, 2021)), we find a close examination of the observed effect sizes informative. Primary analyses yielded quite small (and non-significant) average effect sizes; for example, for every 1 standard deviation unit increase in partner rLSM, the average score on depressive symptoms stayed approximately stable with a wide confidence interval from slight increase to slight decrease (β(SE) = <.001 (.012), CI -.115, .118) and there was an estimated 7% increase in the likelihood of lifetime MDD with a confidence interval ranging from 2.7% lower to 17.8% higher (*OR*(SE) = 1.070(.052), CI = .973, 1.178). The wide confidence intervals suggest substantial uncertainty in the true size (and direction) of the effect. Substantive explanations for a lack of effect could be that interpersonal coordination in language style is not associated with depressive experiences or that this association does not occur in the text message modality. However, as this is the first study of rLSM in text messages (which are characterized by unique conventions such as commonly accepted abbreviations and text lingo not present in past studies), it is also possible that the nature of the text message content obscured potential associatons. We probed this methodological concern through a sensitivity analysis in a subsample of dyads that used more standard English (which we suspected might be better suited for current dictionary-baed methods of computing rLSM), as opposed to more text lingo (which is undetectable using our LIWC dictionary-based method).

In the subsample of dyads who tended to text message using more standard English, those target participants who coordinated language style more also tended to endorse more depressive experiences (both past-year depressive symptoms and lifetime MDD). Moreover, the effect sizes were meaningful: for every 1 standard deviation unit increase in rLSM, depression symptoms increased .2 standard deviations and the likelihood of lifetime MDD increased by 8.2% in the standard English sample. Notably, this was opposite the hypothesized direction, with students evidencing *more* rLSM experiencing more depression, whereas I had hypothesized that students with more depression experiences (and their conversation partners) would evidence less interpersonal coordiantion. Nonetheless, this direction of association is not entirely inconsistent with research to date. For example, Baddley (2012) found a trend that people in remission from MDD coordinated more than never-depressed people. A possible interpretation of the pattern is that when people are depressed, they feel lonely or rejected, and thus they are driven to reengage with others by increasing their interpersonal coordination (Coyne, 1976). One way to understand the current results through the Integrative Interpersonal Model is that more coordination is an effort to counteract other erosive interpersonal processes: Over time, people with depression might learn to coordinate more to build social capital.

It is also possible that the text message modality may mask social skills deficits, perhaps by giving individiauls additional time to consider their responses and "feign" coordination. This possibility of better managing their interpersonal skills and hiding nonverbal indicators of depression such as their posture or tone could mean that asynchronous communication gives depressed people an opportunity to enter an upwards interpersonal cycle. Future research that compares in-person and text coordination and its impact on perceived social support (as done by Baddeley, 2012) could help further explore this possiblity.

A third potential explanation for increased coordination among more depressed students is that rLSM may actually serve as an indicator of a different type of social skill deficit. Our observation of increased coordination (often associated with good outcomes through the mechanism of attention and engagement with another person) is dissonant with previous studies that found deficits in the quality of communication (e.g., more self-focus) among depressed people (Bernard et al., 2015; Smirnova et al., 2018). Several other researchers who have come upon unexpected associations with language style matching reflect that matching appears to be an indicator of the intensity of engagement, not the valence of the interaction, and thus social skills in language style matching could look like too much matching or lack of flexibility in matching across contexts. For example, romantic partners who are more engaged in more intense conflict show more LSM (Bowen et al., 2017).

We strove to enrich the Integrative Interpersonal Model by adding a dyadic component (in recognition that mental illness has impacts on the relational unit including the behavior of partners). We hypothesized that conversation partners of people who have more depressive experiences would also show low interpersonal coordination but did not find evidence to this effect. One possibility was that dyadic effects with depression only occur in close relationships, though sensitivity anayses restricted to just romantic partnerships suggested a similar pattern of (largely null) effects as those seen in the full sample (across all text relationship types). Of note, our romantic relationship sample (overrepresented among non-standard English messages) was not restricted to standard English text messages, and thus may be subject to methodological limitations of computing LSM with non-standard English.

Limitations and Future Directions

This study had many strengths, including a large naturalistic text sample, studying the texting behaviors of both targets and their texting partners, including texts from multiple types of relationships, and examining both depressive symptoms and lifetime MDD. However, several limitations merit consideration and help point to future directions. First, with only a small subgroup of targets in this community (non-clinical) sample who qualified for lifetime MDD (N = 26), we were likely underpowered in detecting effects in this population, and did not have a large enough sample to compare currrent verusus remitted depression. There is some literature to suggest that people with a history of depression, particularly during remission, exhibit higher than average interpersonal coordination (Baddeley, 2012; Bernard et al., 2015). As signs of this pattern emerged again in the current study, it warrants future studies in more clinical samples that can carefully parse apart remitted and current MDD diagnosis in relation to interpersonal coordination of language style.

Second, function word use (and matching) is likely driven by inter-individual differences and as well as intra-individual differences. Future studies can examine within-person variability across who one is speaking to (relational context), what one is speaking about (situational context) and within-person flucutations in depressive symptoms. Third, our predictions focused on between person, linear associations. However, recent research has suggested that flexibility—how much relationships adapt to situations and contexts— may be an important component of whether language style matching relates to positive outcomes, rather than high overall matching alone (Mayo & Gordon, 2020). Future studies could examine whether rLSM changes over time within person, and whether these fluctuations relate to depression.

Fourth, the inherent qualities of text messages—such as common alternate spellings and omission of function words— may preclude or alter the form of language style matching; future directions should consider other indicators of interpersonal coordination in text messages, such as emojis or text lingo. Fifth and finally, our standard English sample might have partners who are different demographically from the primary sample. Although only 3 *targets* were lost from the full sample to the standard English sample, *many dyads* were dropped, resulting in a subset of partners. The standard English sample had lower proportions of Romantic Partners and Friends—peers— but higher proportions of Parents and Others—potentially conversation partners that demand a more formal style of speaking. This highlights that the use of function words may vary by relationship (and, particularly in the case of parents, that “formal” language does not necessary correlate with relationship closeness) and/or the characteristics of conversation partners (e.g., age). Future studies should collect demographic information from partners to disentangle substantive differences across demographic groups from limitations of the rLSM metric when used in text lingo.

Conclusion

This study applied the Integrative Interpersonal Model of Depression to language style matching in text message conversations of college students. Though our primary analyses revealed no evidence of interpersonal coordination effects, sensitivity analysis suggests a surprising positive link between language style matching and depression, where students with more depression experiences are matching their partners more than students with fewer depression experiences. Future studies should examine whether people who are in a current MDD episode, in remission, or who have depressive symptoms coordinate *more* than non-depressed, never-depressed, and less depressed people. This study also joins others in suggesting that language style matching may indicate engaged communication, not necessarily positive communication, and that dynamic and contextual factors of coordination may be important. Lastly, this study puts in question the “match” between the construct of language style matching (that relies on function words that connect formally-structured sentences) and the modality of text messages (in which speaking only in full sentences and even full words is not the norm, at least in the conversations of college students). Given the rich potential of text messages to offer us a window into naturalistic communications, a future direction would be to creatively tap into language style matching with a metric more tailored to the text message modality (e.g., one that includes a dictionary of text lingo and considers alternative aspects of language style such as punctuation and emojis). It would be worthwhile for our field to continue to study how the interpersonal disengagement that characterizes depression may appear and be perpetuated in language, including virtual communication in a digital age.

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APPENDIX A: SMFQ FORMS A AND B

INSTRUCTIONS: These questions are about how you might have been feeling or acting recently. For each question please select how you have been feeling or acting IN THE PAST YEAR. If a sentence was not true about you, select NOT TRUE. If a sentence was only sometimes true, select SOMETIMES. If a sentence was true about you most of the time, select TRUE.

RESPONSE SCALE: 0 = Not true, 1 = Sometimes 2 = True, . = Refuse to answer

Form A	Form B
I felt miserable or unhappy.	I felt miserable or unhappy.
I didn't enjoy anything at all.	I didn't enjoy anything at all.
I felt so tired I just sat around and did nothing.	I felt so tired I just sat around and did nothing.
4 I was very restless.	I felt so fidgety or restless.
I felt I was no good anymore.	I felt I was no good anymore.
6 I cried a lot.	I had crying spells.
I found it hard to think properly or concentrate.	I found it hard to think properly or concentrate.
8 I hated myself.	I didn't like myself.
9 I was a bad person.	I felt bad about myself.
I felt lonely.	I felt lonely.
I thought nobody really loved me.	I thought nobody really loved me.
12 I thought I could never be as good as other people.	I did not feel like I was as good as other people.
13 I did everything wrong.	I thought my life had been a failure.

Note. The SMFQ was administered in two different versions randomly assigned within the sample; one version was the original scale (left column above) and the second had half of the item stems altered for wording but not meaning (right column above; shaded items differ) with the same instructions and response scale. I harmonized these items using moderated nonlinear factor analysis (MNLFA; Bauer, 2017; Bauer & Hussong, 2009; Curran & Bauer, 2011) an iterative model-testing and scoring procedure that takes into account potential differential item functioning across groups (in this case survey form). In a similar sample, MNLFA on these items yielded high internal consistency ($\alpha = 0.91$ in Test Form A; $\alpha = 0.92$ in Test Form B) and test–retest reliability ($\beta = 0.80$ in Test Form A; $\beta = 0.85$ in Test Form B; Cole & Hussong, 2020).