Incorporating Social Network Variables into Relational Turbulence Theory:

Popping the Dyadic Bubble

by

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ABSTRACT

Relational turbulence theory (RTT) has primarily explored the effects of relational uncertainty and partner interdependence on relational outcomes. While robust, the theory fails to account for uncertainties and perceived interdependence stemming from extra-dyadic factors (such as partners' social networks). Thus, this dissertation had two primary goals. First, scales indexing measures of social network-based relational uncertainty (i.e., network uncertainty) and social network interdependence are tested for convergent and divergent validity. Second, measurements of network uncertainty and interdependence are tested alongside measures featured in RTT to explore predictive validity. Results confirmed both measurements and demonstrated numerous significant relationships for turbulence variables. Discussions of theoretical applications and future directions are offered.

Keywords: uncertainty, turbulence, social networks, structural equation modeling

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INTRODUCTION AND LITERATURE REVIEW

One of the most tenured elements of interpersonal communication is uncertainty (e.g., Kahneman & Tversky, 1982; Shannon & Weaver, 1964). As a construct, uncertainty has been considered an experience that people avoid if they can, and reduce if they must (Berger & Calabrese, 1975; Brashers, 2001; Emmers & Canary, 1996). Decades of research stemming from Berger and Calabrese's (1975) uncertainty reduction theory have sought to parse the mechanisms that cause, exacerbate and stem from experiences of uncertainty (e.g., Afifi & Weiner, 2004; Solomon & Knobloch 2004; Sunnafrank, 1986). As a measured variable, uncertainty has been used as a partial determinant of emotion (Brashers, 2001), cognitions (Solomon & Samp, 1998), and communicative episodes (Theiss & Solomon, 2006a) within close relationships.

Following the lead of most relationship scholars, the bulk of uncertainty research foregrounds dyadic interdependence (e.g., Baxter & Bullis, 1986; Berscheid, 1983). That is, it largely assumed that uncertainty in a relationship exists within, and stems solely from, dyadic interaction. On the other hand, extant work clearly indicates that social network members (i.e., a couple's friends, family, and peers) represent important determinants of experiences of uncertainty (e.g., Parks, Stan, & Eggert, 1983; Sprecher & Felmlee, 1992, 2000). In addition, network members purposefully influence romantic relationships (Sprecher, 2011) and can either foster or inhibit intra-network interdependence (Surra, 1988). Thus, social network members may serve as integral players in the formation and/or dissolution of dyadic relationships (Duck, 1982).

Given their primarily dyadic focus, interpersonal communication research can benefit from the incorporation of the couple's social network into existing relational theories. Relevant scholarship has demonstrated that romantic relationships occur within the larger context of a couple's social network(s) (Parks & Adelman, 1983; Sprecher & Felmlee, 1992). Classical theories, such as uncertainty reduction theory (Berger & Calabrese, 1975) and predicted outcome value theory (POV; Sunnafrank, 1986), as well as modern theories, such as the theory of motivated information management (Afifi & Weiner, 2004), and uncertainty management theory (Brashers, 2001) could increase their explanatory and predictive strength by taking incorporating social network variables.

One such framework that might be improved by the inclusion of network variables, from both a predictive and explanatory perspective, is relational turbulence theory (RTT) (Solomon, Knobloch, Theiss, & McLaren, 2016). Turbulence theory identifies uncertainty (specifically relational uncertainty) and interdependence (i.e., partners' ability to interfere and/or facilitate individual goal achievement) as generative mechanisms that influence cognitions, emotions, and communicative episodes (e.g., Theiss & Nagy, 2013; Knobloch & Theiss 2011). In RTT, experiences of uncertainty and interdependence are typically viewed as exclusively dyadic. However, there is thus ample reason to expect that the social networks surrounding a couple influence relational turbulence and outcomes. For example, early tests of the relational turbulence *model* (RTM) have linked the (perception of) helping and hindering behaviors of network members to experiences of relational uncertainty (Knobloch & Donovan-Kicken, 2006). Said differently, perceptions of network behaviors may lead people to experience relational uncertainty.

Extant work supports the notion that social networks can influence both dyadic perceptions (Parks et al., 1983, Sprecher, 2011), as well as relational outcomes (Agnew et al., 2001; Xu & Burleson, 204). Interpersonal communication theories, however, have neglected this important source of influence. Therefore, the ultimate goal of this study is to use RTT (Solomon et al., 2016) as an example of the ways that social networks function in interpersonal communication theory. In other words, this dissertation will examine extra-dyadic sources of relational uncertainty and interdependence as potential indicators of relational turbulence. The results will ultimately encourage incorporation of social network variables into other existing interpersonal communication theories.

Social Networks and Relational Turbulence: Background and Significance

Despite evidence of extra-dyadic influence on romantic partnerships, the vast majority of interpersonal theories focus only on dyadic interactions (e.g., Afifi & Weiner, 2004; Berger & Calabrese, 1975; Brashers, 2001; Solomon et al., 2016). The lack of research on the role of social networks in romantic relationships is curious given the importance of friends, family, and peers in managing a variety of crises such as: delinquent behaviors (Oetting & Donnermyer, 1998), coping with illness (Kroenke et al., 2013), and managing stress (Cohen & Willis, 1985). What is more, substantial relational scholarship has revealed that couples' relational turmoil and successes are not exclusively a result of dyadic process (Duck, 1982; Parks et al., 1983; Sprecher, 2011). More salient to the present study, social network members can both interfere with (Sprecher, 2011) and facilitate (Surra, 1988) relational perceptions and therefore, progression. What is more, social network members can be a unique source of uncertainty that, ultimately, influence experiences of relationship-specific uncertainty (Stein, Mongeau & Truscelli, 2017).

Research detailing the influence and uncertainty generated by network members in both fledging and established dyads (e.g., Sprecher & Felmlee 1992, 2000) indicates that interpersonal theories generally, and RTT (Solomon et al., 2016) specifically, could benefit from a social network-based lens. Relational turbulence theory is a three-phase theory that attempts to explain the turmoil that couples face as a result of perceptions of uncertainty and influence from their partners (see Solomon, Weber, & Steuber, 2010, for a review). Turbulence researchers have occasionally introduced social network factors as *outcomes* of turbulence (e.g., Knobloch & Donovan-Kicken, 2006); however, the driving mechanisms within turbulence theory are entirely subsumed within a given dyad.

Thus, the primary goal of this dissertation is to explore how *social network-based relational uncertainty* (i.e., network uncertainty; Stein et al., 2017) is related to RTT processes and outcomes. Such exploration will involve examining the convergent, divergent, and concurrent validity of measures of network uncertainty. Similarly, recently developed measures of *social network interdependence* (i.e., network interference and facilitation, Stein, 2017) will be tested for convergent, divergent, and concurrent (i.e., construct) validity in the context of RTT. In other words, this study is based on the premise that social-network related variables significantly influence relational cognitions, emotions, and communicative episodes that generate relational turmoil above and beyond dyadic variables.

Fulfilling this study’s primary goal will involve unpacking two new variables (network uncertainty and network interdependence) within an existing theoretical frame.

Accordingly, a detailed description of the theoretical and conceptual backdrop of this dissertation is necessary. Therefore, the next section describes RTT. Following this description, a review of how social networks influence close relationships (particularly concerning the uncertainty that they create) will be offered. A detailed conceptual definition of network uncertainty and network interdependence will then be developed, followed by a discussion of existing research of these variables. Finally, an explanation of the possible role of network uncertainty and network interdependence in RTT processes will be offered. Given that turbulence theory serves as the theoretical anchor for this study, it is discussed, in detail, first.

Relational Turbulence Theory and the Relational Turbulence Model

Relational turbulence *theory* represents the cumulation of 15 years of tests and conceptual developments of the relational turbulence *model*. The primary difference between the RTM and RTT lies in the idea that the former describes associations between variables under varying conditions, whereas the latter explains relationships in terms of generative mechanisms. Initially, the RTM assumed that partners' experiences of relational uncertainty stemmed from fluctuations in intimacy, peaking at moderate levels (Solomon & Knobloch, 2001). Later, RTM scholars argued that turbulence stemmed from some form of relational transition, such as the transition from casual to serious dating (Knobloch, 2006), empty-nest parents (Theiss & Nagy, 2013), or post-deployment military couples (Theiss & Knobloch, 2014). In its most recent iteration, turbulence *theory* does not require such prerequisites (Solomon et al., 2016).

Through many tests and extensions of the RTM, turbulence researchers (Solomon et al., 2016) compiled a theory that seeks to explain the ways in which *relationships* *parameters* influence experiences of *specific communication episodes*, ultimately leading to a series of *cumulative effects and outcomes* (see Figure 1 for predicted relationships between variables; Solomon et al., 2016). Each of the theory's three panels depicts relationships between variables that, when combined, compose the turbulence process. This review will discuss the elements of each panel and the previous tests that led to their inclusion.

Relationship Parameters

The left-hand panel of Figure 1 portrays RTT's two generative mechanisms (i.e., variables that cause outcomes): relational uncertainty and interdependence. First, in RRT, relational uncertainty is defined as "the degree of confidence people have in their perceptions of involvement within an interpersonal relationship" (Knobloch & Solomon, 1999, p. 797). The term relational uncertainty serves as an umbrella term that encompasses three elements: the self, the partner, and the relationship (Berger & Bradac, 1982; Knobloch & Solomon, 1999). The three elements of relational uncertainty predict a number of unique outcomes and, thus, require individual attention.

First, s*elf uncertainty* is the doubt experienced about one's own involvement in a relationship (e.g., *do I love my partner? Am I committed to him/her? Do I want him/her in my life?*; Knobloch & Solomon, 1999). Self uncertainty is positively related to outcomes such as communicative directness about irritations (Theiss & Solomon, 2006a) and depressive symptoms (Knobloch & Knobloch-Fedders, 2010). Self uncertainty is also negatively associated with relational involvement (Knobloch, Miller, Bond, & Mannone, 2007). In many cases, self uncertainty related to relational perceptions more strongly than did partner and relationship uncertainty. For example, self uncertainty is the strongest indicator of marital quality (Knobloch, 2008), affiliation and involvement (Knobloch et al., 2007), and relationship satisfaction (Knobloch & Theiss, 2011). Additionally, in cases where one or more partners in a relationship are depressed, self uncertainty (and not partner or relationship uncertainty) mediates the relationship between depressive symptoms and relationship satisfaction (Knobloch & Theiss, 2011).

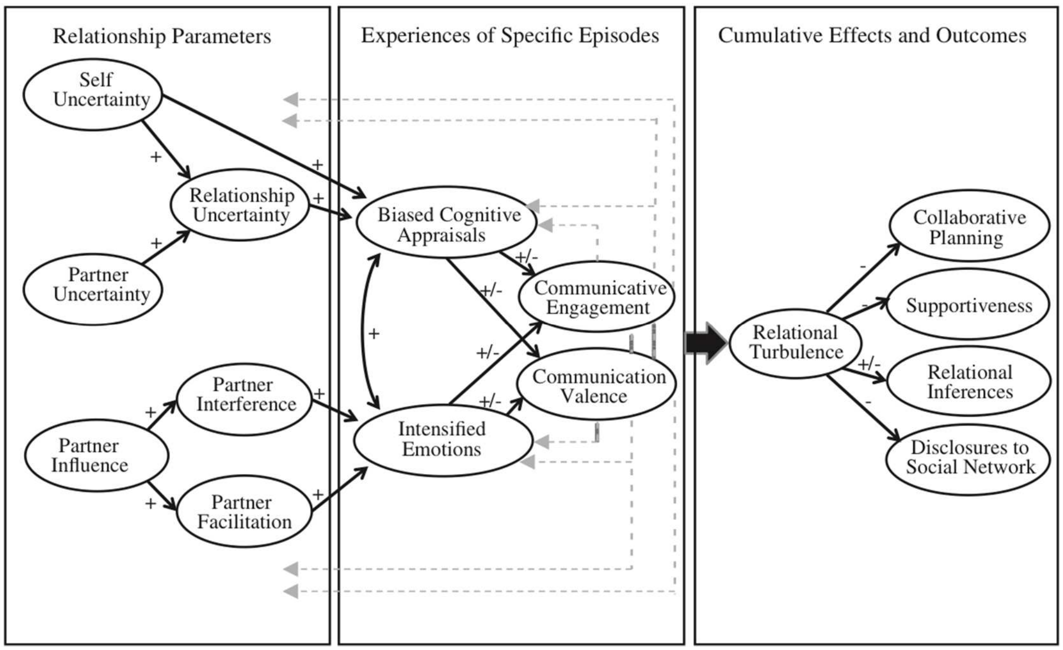

Figure 1. Relationships between variables in relational turbulence theory.

Partner uncertainty is the concern that people have about their partner's involvement in their relationship (e.g., *Does my partner care about me? Does he/she want to be with me?*; Knobloch & Solomon, 1999). The influence of partner uncertainty, on the whole, is not as frequent or strong as those of self uncertainty (e.g., Knobloch, Solomon, & Cruz, 2001; Theiss & Solomon, 2006a). That said partner uncertainty shares negative associations with numerous relational outcomes including relational judgments (e.g., immediacy, similarity, and trust; Knobloch & Solomon, 2005) and perceived partner responsiveness (Theiss & Nagy, 2013). Unlike self uncertainty, the majority of partner uncertainty effects are indirect (e.g., Theiss & Nagy, 2013; Theiss & Solomon, 2006a). In other words, the relationship between partner uncertainty and relational cognitions/behaviors are mediated by relationship uncertainty. Thus, in turbulence theory, partner uncertainty influences variables through relationship uncertainty, to be discussed below.

According to RTT, self and partner relationship both positively contribute to experiences of *relationship uncertainty*, which is the concern that a person has about his/her relationship as a unit (e.g., *is this relationship going to work out? Will we be able to last for the long haul?*; Knobloch & Solomon, 1999). The relationship between self/partner uncertainty and relational uncertainty is proposed to be linear (Solomon et al., 2016). In other words, in order to experience relationship uncertainty, one must first experience self and/or partner uncertainty (Solomon et al., 2010). Therefore, relationship uncertainty mediates the relationship between self/partner uncertainty and a bevy of outcome variables. Specifically, it has been demonstrated that relationship uncertainty typically fully mediates effects of partner uncertainty and partially mediates effects of self uncertainty on variables such as frequency of relationship talk (Knobloch & Solomon, 2005), discussions of irritations (Theiss & Solomon, 2006a), and romantic jealousy (Theiss & Solomon, 2006b). It is important to note that, *relational uncertainty* is a higher-order construct that encompasses self, partner, and relationship uncertainty, but does not appear in tests of the model.

For the present study, relational uncertainty (i.e., self, partner, and relationship uncertainty) will serve as a central focus of analysis. Self and partner uncertainty are viewed as exogenous variables in turbulence theory (i.e., they generate turbulence processes and outcomes; Solomon et al., 2016). Whereas the current version of RTT assumes that self and partner uncertainty are causal variables, a primary goal of this dissertation will be to identify network-based uncertainty as a predictor of both self and partner relationship.

The second relational parameter in RTT (seen in the lower portion of Figure 1's first panel) perceived is interdependence between partners (Berscheid, 1983). Interdependence, in RTT is described as the extent to which a person's partner "influences his or her everyday activities" (Solomon et al., 2016 p. 8). Berscheid (1983) describes dyadic interdependence as emerging from a dual chain of events. Partner A's chain of events is causal (i.e., one event happens which leads to another, then a third, etc.). Simultaneously, partner B has a chain of events that co-occurs with partner A's. This progression of events is known as a "causal interchain sequence" (p. 138). Interdependence is the degree to which partner A's interchain sequence influences partner B's interchain sequence, and vice-versa.

Berscheid (1983; and RTT) argues that interchain influence can stem from two relational behaviors: interference and facilitation. *Partner interference* is the degree to which partner A hampers Partner B's ability to reach everyday goals (Berscheid, 1983; Knobloch & Solomon, 2004). Partner interference produces increased perceptions of both relational turmoil and negative emotions in relationships—effects that occur at both the actor and partner levels (Knobloch & Theiss, 2010). Partner interference also positively relates to negative appraisals of partners (Solomon & Knobloch, 2004) and negatively relates to both effective conflict management strategies and perceptions of partner responsiveness (Theiss & Knobloch, 2014).

The second aspect of partner interdependence is *partner facilitation*, or the degree to which partner A aids in the accomplishing of partner B's everyday goals (Berscheid, 1983; Solomon & Knobloch, 2004). Unlike interference and relational uncertainty, which are markers of relational turbulence, partner facilitation mitigates turbulent experiences. For example, partner facilitation is positively associated with the perception that social network members aid in relational development (Knobloch & Donovan-Kicken, 2006). Moreover, partner facilitation is negatively associated with experiences of sadness and jealousy (Knobloch, Miller, & Carpenter, 2007).

Interestingly, partner facilitation and partner interference correlate positively at the bivariate level; however, this relationship turns negative when controlling for neutral experiences of influence (Knobloch & Solomon, 2004). In other words, when holding the quantity of influencing behaviors constant, interference and facilitation produce opposite emotional and cognitive effects. Much like relational uncertainty, perceptions of partner interdependence are not necessarily tethered to a relational transition in RTT. Thus, experiences of relational uncertainty and partner influence may be spurred by specific events and cognitions in addition to transitions.

Relational uncertainty and partner interdependence comprise the first panel of turbulence theory. Together, these two mechanisms generate couples' cognitions, emotions, and eventually, communicative episodes. Individual tests of the RTM have revealed that both relational uncertainty and partner interdependence can lead to heightened emotional responses (Knobloch & Theiss, 2010), biased relational cognitions (Theiss & Nagy, 2013), and both the ability to process (Knobloch et al., 2007) and produce (Knobloch, 2006) information. The second panel of RTT attempts to specify these relationships.

Experiences of Specific Communication Episodes

The second panel of RTT (see Figure 1) is certainly the most interactive, in that it ends with a couple's communicative experiences. In the upper portion of this panel, both self and relationship uncertainty are predicted to positively influence *biased cognitive appraisals*, which are "the distorted assessments of a specific situation" (Solomon et al., 2016, p. 6). Biased cognition can come in many different forms. As illustrated in the original turbulence model (Solomon & Knobloch, 2004), all three elements of relational uncertainty positively predict negative appraisals of one's partner. Theiss and Knobloch (2014) also demonstrated that relationship uncertainty positively influences the perception that one's relationship is in turmoil. In addition, self and relationship uncertainty are positively and directly associated with the perception that relational talk is threatening (Knobloch & Carpenter-Theune, 2004; Theiss & Nagy, 2013). It is important to note that relational uncertainty leads to a *perception* of these negative experiences. There may be no change in turmoil or danger in one's relationship than usual; however, the presence of relational uncertainty provides an atmosphere where polarized appraisals are most likely to occur.

Much in the way that relational uncertainty influences the partners' appraisals about each other and their relationships, RTT assumes that the elements of interdependence (i.e., interference and facilitation) predict *intensified emotional experiences*. Notably, although both interference and facilitation are both predicted to relate to emotional reactions, the valence of those relationships differ. For example, partner interference is positively associated with negative emotions (e.g., anger, sadness, and fear; Knobloch, Miller, and Carpenter (2007)—a finding that remained true across both actor and partner effects for anger and sadness (Knobloch & Theiss, 2010). It has also been revealed that interference from partners is positively related to depressive symptoms (Knobloch & Theiss, 2011) and experiences of emotional jealousy (Theiss & Solomon, 2006b).

On the other hand, partner facilitation inversely contributes to the experience of negative emotions (Knobloch, Miller & Carpenter, 2007) and is positively associated with perceptions of intimacy (Knobloch & Solomon, 2004). As such, it is likely that partner facilitation leads to more positive emotional reactions. Additionally, Berscheid (1983) noted that facilitation from partners fosters positive relational experiences and feelings. Turbulence theory, however, is more commonly concerned with the negative emotions that arise from a partner's interference and/or facilitation (see Solomon & Theiss, 2011).

According to RTT, biased appraisals and intensified emotions both lead to the final element of the second phase: communication. These relationships can be viewed in the right-hand side of the second panel of Figure 1. Turbulence theory conceptualizes communication in two ways: *communication engagement* and *communication valence*. In RTT, however, the nature of the associations (i.e., whether relationships are positive or negative) of these predictions is unspecified.

On one hand, negatively-biased cognitions (such as negative appraisals or decreased relationship satisfaction) have been shown to increase the directness of communication about irritations (Theiss & Nagy, 2013). Similarly, intensified negative emotions (such as anger, sadness, and fear) increase communicative enactment (Theiss & Solomon, 2006a).

Conversely, negatively-valenced cognitions and/or emotions may inversely relate to the enactment of communication episodes (Solomon et al., 2016). For instance, Solomon and Samp (1998) revealed that those who perceive their relational problems as more "real" voice less complaints (i.e., the chilling effect; Roloff & Cloven, 1990). McLaren (2008) extended this work by noting that hurtful emotions can lead to disaffiliation (i.e., communicative avoidance). Similarly, Theiss and Solomon (2006b) found that emotional jealousy can lead to decreased directness of communication about jealousy.

It would seem as though cognitions and emotions can spark differing levels of communicative engagement, depending on how and why they are experienced. This is problematic for a communication theory. Without specified directionality for a theory's propositions, the predictive value of that theory is tarnished. Given that RTT is a communication theory, the role of communication is in need of further probing and specification.

Turbulence research is limited concerning communicative valence; however, scholars have shown that both negative cognitions (Miller & Bradbury, 1995) and emotions (McLaren & Steuber, 2013) produce more negatively-valenced communication episodes. McLaren and Steuber found that feelings of hurt and anger (i.e., intensified emotions) led to increased distributive (i.e., destructive)). Additionally, anger and sadness positively correspond with negative communication, whereas joy and happiness are associated with positive interactions in breast cancer patients (Weber & Solomon, 2007).

More generally, partners with intensified negative emotions engage in more frequent conflict and experience increased post-conflict anxiety (Aureli, 1997). Partners also exhibit the tendency to reciprocate both positive and (even more so) negative emotions during communicative episodes (Gaelick, Bodenhausen, & Wyer 1985). Therefore, both appraisals and emotions can, in part, determine the positivity/negativity of a communicative encounter.[1]

Cumulative Effects and Outcomes

In Figure 1, communicative episodes occur at the right-hand side of the second panel. The third and final panel focuses on the outcomes generated by repeated communication episodes. It is argued in RTT that the enactment and valence of communication episodes, over time, lead to long-lasting perceptions of turbulence.

Whereas previous conceptualizations of turbulence were more episodic in nature (e.g., Solomon et al., 2010), Solomon and colleagues (2016) define turbulence as a "global and persistent evaluation of the relationship as tumultuous, unsteady, fragile, and chaotic that arises from the accumulation of specific episodes" (p. 12). In other words, specific relational events (i.e., communicative episodes) eventually contribute to ongoing relational perceptions. Turbulence theory makes specific efforts to distinguish experiences of relational turbulence from (for example) biased cognitions that people experience and that appears in the second panel of Figure 1. Specifically, relational

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[1]Relational turbulence theory also proposes a *feedback loop* (represented by dotted lines in Figure 1). Communicative episodes can subsequent levels of uncertainty/interdependence as well as subsequent appraisals and emotional reactions. In other words, the feedback loop proposes that specific communication episodes can alter the relationship parameters that impact future turbulent experiences. These propositions will not be tested by this study.

turbulence is said to emerge from interpersonal dynamics, whereas biased cognitions give way for such macro evaluations to occur.

The ongoing relational evaluations that couples make (i.e., turbulence) contribute to the long-term plans that people have for their relationships. Scholars report that relational turbulence leads to decreased partner supportiveness (Trope & Liberman, 2003), decreased collaborative planning (Harrist & Waugh, 2002), decreased disclosures to social networks (Knobloch & Donovan-Kicken, 2006), and modified relational inference (Theiss & Solomon, 2006b).

To summarize, RTT proposes that relational uncertainty and perceptions of partner interdependence generate biased cognitions and heightened emotions, respectively. These perceptions then lead to the amount and valence of communication episodes, resulting in broad perceptions of relational turbulence, which in turn, influence long term goals and perceptions (Solomon et al., 2016).

The process leading up to turbulence, according to turbulence theory, is exclusively dyadic. The goal of this dissertation is to expand the scope of RTT to include social-network based variables in the generative mechanisms of relational uncertainty and interdependence. It is through this endeavor that the heuristic value of RTT can be increased. Prior to exploring how network variables influence RTT variables, it is important to discuss the research that has explored network perceptions as indicators of dyadic perceptions and relational outcomes.

How Social Networks Influence Close Relationships

Considerable research has described the influence a couple's social networks can have upon their relationship (see Parks et al., 1983; Sprecher & Felmlee 1992, 2000).

Together, this research indicates that social network members play integral roles in initiating (Connolly & Johnson, 1996), developing (Parks & Adelman, 1983), maintaining (Xu & Burleson, 2004), and dissolving (Agnew, Loving, & Drigotas, 2001) relationships. Below a detailed summary of how social networks influence dyadic relationships is offered.

Social Network Characteristics and Behaviors

Scholars have noted the difficulty in developing an all-encompassing definition for the term *social network* (e.g., Shinn, Lehmann, & Wong, 1984). However, this hurdle has not stopped researchers from exploring the various characteristics that make up social network. Two common attributes of a social network are a desire for continued interaction (interpersonal or small group; face-to-face or mediated), and an overall affinity for group members (Hill & Dunbar, 2003). Most typically, researchers who study a person's *social network* ask respondents to either describe "kin" with whom they are close (e.g., Parks et al., 1983), or simply ask about friends and family members (e.g., Felmlee, 2001). When Sprecher (2011) asked participants to report on a "network member," friends were the predominant choice (as opposed to family members, neighbors, or coworkers). That said a social network can consist of friends, family members (by blood, by marriage, or even fictive kin), co-workers, and neighbors (Hill & Dunbar, 2003).

Like dyads, social networks (and the individuals who compose them) are interdependent. Specifically, Surra (1988) draws from the concept of *structural interdependence* to describe the "placement of pair relationships within the network including both the simple presence or absence of pair relationships…as well as the overall pattern of those relationships" (Milardo, 1986, p. 157). Using this conceptual definition, Surra (1988) distinguished a number of interdependent attributes of social networks. Her review noted five specific features of social network independence: *size* (the number of different people that an individual interacts with), *density* (the actual number of connections that a person has compared to the maximum number of potential connections), *clustering* (the extent to which subgroups exist within a network), *reachability* (the degrees of separation between a given network member and every other member), and *overlap* (the extent to which members of one person's network are members of another person's network). Turning to Berscheid's (1983) conceptualization of interdependence, it is reasonable to assume that dense clusters of reachable network members who overlap with one another have the potential to both interfere with and facilitate each other's daily goals. This may even involve impacting the romantic relationships that network members engage in.

Perhaps due in part to network interdependence, social network members are perceived to influence both individual and relational outcomes in a number of ways. One individual outcome is through the sway that networks have over an individual's deviant behavior (Oetting & Donnermeyer, 1998). Specifically, depending on the nature of the bond(s), an adolescent's friends, family, and peers can either increase or decrease the likelihood of substance abuse (Dickens, Dieterich, Henry, & Beauvais, 2012; Smith et al., 2014). Moreover, positive social interactions have shown to improve quality of life for individuals with a grave illness (such as cancer; Kroenke et al., 2013). Additionally, social support is integral in assuaging psychological stressors (Shinn, Lehmann, & Wong, 1984). One example of this is in the health context; in which invited social support from network members can decrease stress, psychological distress, and even physical symptoms (for reviews see Cohen & Syme, 1985; Sarason & Sarason, 2013).

Finally, the perception that network members are interfering with one's relationship can lead to heightened levels of relational uncertainty (Knobloch & Donovan-Kicken, 2006). This finding has received additional support. Social network members report intentional attempts to hinder relationships that they do not approve of (Sprecher, 2011; Surra, 1990). Network members also tend to aid in the development of relationship that are perceived as more successful and intimate (Knobloch & Donovan-Kicken, 2006). This implies that both relational partners and network members themselves see social networks as integral players in a dyadic relationship. That said, myriad research has specified the ways in which perceptions of social network involvement can help or hinder an individual's relational development, as articulated below.

Network Influence on Relationship Satisfaction and Quality

Several studies have attempted to identify the ways in which social network members influence relationship satisfaction and quality. Several of these studies have explored the ways in which various forms of network interdependence (see Surra, 1988) produce relational outcomes. Agnew and colleagues (2001), for example, reported that greater network overlap positively contributes to levels of couple commitment, investment, and relationship satisfaction. Additionally, closeness (for women) and insecurity (for men) toward one's own network (elements of network density) are positively associated with feelings of closeness between partners (Neyer & Voigt, 2004).

Network size also facilitates engagement in romantic relationships for adolescents (Connolly & Johnson, 1996).

It is possible that there is interplay between Surra's (1988) elements of network interdependence and RTT's (Solomon et al., 2016) measurements of interdependence (i.e., interference and facilitation). The characteristics of network interdependence likely allow for interfering and facilitating behaviors to occur within networks, potentially altering relational perceptions and interactions.

In addition to interdependence, network approval and support are widely studied determinants of dyadic quality. Most notably, Parks and colleagues (1983) demonstrated that support from participants' own (and their partners') networks positively influenced romantic involvement. Sprecher and Felmlee (1992) extended these findings by showing that network support is associated with increased levels of love, satisfaction, and commitment cross-sectionally (but not longitudinally). In marital contexts, emotional support from network members positively influences marital satisfaction (Xu & Burleson, 2004). Finally, Sprecher (2011) noted that perceptions of partner interference and facilitation are related to perceptions of network approval (negative and positively, respectively). Thus, perceptions of network approval and support (or lack thereof) are related to the helping/hindering behaviors reported by network members.

Scholars have also documented the potential negative influence of networks on relationship satisfaction. Neyer and Voight's (2004) findings suggest that as people become more insecure (i.e., experience uncertainty) about their network relationships, they also tend to become more insecure with their romantic relationships. Moreover, jealousy of a partner's online social network members can increase monitoring behaviors as well as relationship-based jealousy (Utz & Beukeboom, 2011). Network members who intentionally express disapproval of a relationship are more likely to believe that they negatively correlate with relationship strength (Sprecher, 2011). Together, these results speak to the influence that negative network behaviors can hold over relational perceptions.

Other research has explored the *Romeo and Juliet* effect where parental and peer disapproval serves to increase feelings of love and intimacy (Driscoll, Davis, & Lipetz, 1972). Although Driscoll and colleagues found support for the Romeo and Juliet effect, subsequent studies have failed to replicate this finding (e.g., Parks et al., 1983; Sinclair, Hood, & Wright, 2014). For example interfering network behaviors negatively associate with relational quality (Sinclair et al., 2014), whereas network approval tends to facilitate relational longevity (Sprecher & Felmlee, 2000). As such, it is safe to conclude that perceptions of network approval and support are both positively associated with relational quality.

Interestingly, network-dyad interaction influences both the quality of dyadic relationships, and the quality of network relationships (including a partner's network). Relationship support from one's own network positively correlates with attraction to a partner's network (Eggert & Parks, 1987). Similarly, the amount of (presumably positive) communication enacted with one's own network can increase levels of attraction to the partner's network (Parks et al., 1983). Felmlee (2001) found that approval from one social circle (e.g., friends) can mitigate the effect that another circle's disapproval (e.g., family) has on relational quality. Put differently, approval from friends can bolster relational quality even if family members disapprove (and vise versa).

When combined, the studies discussed above demonstrate some of the ways that social network involvement can influence relational cognitions, perceptions, and maintenance. In other words, perceptions of network influence may be partial determinants of relational cognitions and behaviors. For example, it may be that perceived interference/facilitation from network members foster or hinder (respectively) negative emotions. Uncertainty about network members, such as jealousy (Guerrero & Andersen, 1998), or a fear of not being liked by network members (Sprecher & Felmlee; 1992, 2000) may result in the questioning of one's own relationship state.

Although quality and satisfaction are two important elements of a dyadic relationship, it is equally important to discuss behaviors that result from such evaluations. Searches for the ways in which network members influence communication between partners (such as the enactment or valence of communicative episodes; Solomon et al., 2016) did not produce substantive results. However, previous research has outlined the ways in which social networks can influence relational longevity. Given that productive communication is a key indicator of relational success (Knobloch & Solomon, 2003; Rusbult, Drigotas, & Verette, 1994; Theiss, 2011), exploring the social network's effect on relational longevity is fitting. Below is a discussion of this literature.

Network Influences on Relational Persistence

It has been documented that network members intentionally engage in relationship-altering behaviors (both helping and hindering) because they *believe* that they can influence the durability of a relationship (Sprecher, 2011). This raises the question: Do network members *actually* influence the longevity of their members' close relationships? Considerable research has explored this question, and indicates that both network interdependence and network support/approval influence relationship persistence.

One crucial way that network members influence relational persistence is through the provision of support and acceptance of a relationship. Felmlee (2001) noted that breakups are less likely in relationships that receive approval and/or support from surrounding networks. Additionally, liking of a partner's network is negatively associated with subsequent breakup rates (Sprecher & Felmlee, 2000). On the other hand, network members may purposefully withhold support and approval in the hopes of facilitating a breakup, especially if they perceive that the relationship is hindering network interaction (Milardo, Johnson, & Huston, 1983). Taken together, these studies demonstrate that perceptions of network support and approval can influence relational success.

It also appears that the *perception* of network approval/support contributes strongly to stay/leave patterns. For example, Felmlee (2001) noted that over one-third of couples who break up indicate that the network did, in some way, contribute to that dissolution. More specifically, Agnew and colleagues (2001) noted that 27% of the variance in breakup tendencies is attributed to perceptions of network approval and support. This trend has been shown to continue over time as well. In a five-wave longitudinal study, Sprecher and Felmlee (2000) reported that negative network evaluations at one time were related to breakups at a later time. In other words, the perception about a network's role in relationship development has more sway over relationship trajectory than actual network involvement (Duck & Pond, 1989).

One reason that networks can influence relational longevity is because they are interdependent (Surra, 1988). For example, couples with high levels of network overlap (an element of network interdependence) are more likely to be together at a six-month follow-up than those with low network overlap (Agnew et al., 2001). On the other hand, when couples break up, they often report subsequent decreases in network overlap (Sprecher & Felmlee, 2000). As the authors describe, “as a couple becomes more involved and interdependent, the partners’ networks will also become more intertwined and interdependent” (Sprecher & Felmlee, p. 326). Said differently, it is possible that network members experience the same kind of interdependence that romantic partners do (Berscheid, 1983).

Because network overlap is a result of increased familiarity between partners’ networks (Sprecher & Felmlee, 2000), it is a likely indicator of reduced relational uncertainty for both partners (as defined by Knobloch & Solomon, 1999). Relational uncertainty shares a negative association with relationship satisfaction (Solomon & Theiss, 2008). Thus, reductions of relational uncertainty stemming from one’s (or a partner’s) network may result in perceptions of network approval ultimately leading to a more successful relationship (Felmlee, 2001). Finally, Parks and Adelman (1983) reported that levels of communication with a partner’s network reduced uncertainty about relational state three months later. This same study revealed that amount of communication and support from a partner’s network reduced the chance of breakup at a later time.

In sum, social network members can significantly affect the quality and persistence of their relationship. It should be noted that network members tend to bear greater influence on women’s breakup decisions than men’s (Agnew et al., 2001; Sprecher & Felmlee, 1992, 2000). Moreover, in most cases, one’s own network is usually more influential than a partner's network (e.g., Eggert & Parks; 1987; Parks et al., 1983; Sprecher & Felmlee, 1992). These differences are important moving forward for framing the nature and magnitude of network involvement on dyadic inferences and relational behaviors. Even so, both social networks in a relationship are capable of influencing dyadic patters for both members of a couple.

The clear connection between network involvement, relational quality, and relational longevity suggest that, much in the way people can experience relational uncertainty (Knobloch & Solomon, 1999), people may experience unique uncertainties pertaining to perceptions of one's (partner's) network. In turn, uncertainties about network members may eventually impact relational evaluations (i.e., relational uncertainty). Moreover, interfering (Sprecher, 2011) and facilitating (Felmlee, 2001) behaviors from network members may too influence relationship parameters (such as perceived interdependence with one's partner). As such, network variables (such as uncertainty and interdependence) may be associated with relational perceptions (i.e., relational uncertainty and partner interdependence) as well as cognitive and emotional reactions. In other words, the variables in RTT may be influenced by and/or related to social network variables. Ongoing research has sought to explore this query. A summary of these findings is to be described below.

Review of Network Uncertainty and Interdependence

Because social networks can dramatically alter relational cognitions and behaviors (Agnew et al., 2001; Parks et al., 1983; Sprecher & Felmlee, 1992), it is reasonable to assume that interpersonal communication theories could expand their scope through the inclusion of network-focused variables. The primary heuristic contribution of this dissertation will accomplish just that. Specifically, scales measuring network uncertainty and network interdependence will be tested using an existing theory (i.e., RTT; Solomon et al., 2016). These network-based variables have been conceptualized and operationalized in several studies. Below is a description of this program of research.

Defining Network Uncertainty

Initially, uncertainty was positioned as global in nature. Early conceptualizations focused on a person's ability to predict or explain how another person might behave during an initial interaction (Berger & Calabrese, 1975). Relational uncertainty, on the other hand, is a degree of confidence that people have in their involvement within a specific ongoing relationship (Knobloch & Solomon, 1999). Drawing from this definition, social network-based relational uncertainty (i.e., network uncertainty) is defined as "the degree of confidence that relational partners have in their networks' acceptance and support of their relationship's development" (Stein & Mongeau, under review, p. 5). Both relational uncertainty and network uncertainty are defined as a degree of confidence. People make appraisals about how their (and their partners') networks acceptance and support – as it relates to the trajectory of their relationship (e.g., Agnew et al., 2001; Sprecher & Felmlee, 2000). Network uncertainty is the confidence that they have in those assessments.

Perceptions of network uncertainty focus on the extent to which network members are perceived to accept and support the development of a relationship. Acceptance can be understood as a broad term that encompasses perceptions of approval (Sprecher & Felmlee, 2000), liking (Parks & Adelman, 1983), and overall positivity concerning a relationship. Perceived support, in this definition, is defined as any and all behaviors that aid in relational maintenance (Sprecher & Felmlee, 1992). Thus, people may be uncertain about the perceptions that network members have toward either member of a relationship, or the relationship all together (acceptance), and/or the behaviors that network members engage in to keep a relationship afloat (support).

Broadly, this definition implies that network uncertainty, much like other forms of uncertainty, is a negative experience that could be potentially damaging to relationships. Additionally, network uncertainty does not assume that network members *actually* negatively evaluate or disapprove of the relationship in question. Rather, network uncertainty represents a lack of confidence concerning (i.e., a perception of) network's attitudes or behaviors. Such perceptions may lead to a slew of negative evaluations, emotions, or communicative enactments.

Sources of Network Uncertainty

In an initial investigation of network uncertainty, Stein and Mongeau (under review) emulated Knobloch and Solomon's (1999) methods to uncover (Study 1) and measure (Study 2) sources of network uncertainty during initial interactions. Study 1 used open coding (Strauss & Corbin, 1990) to generated eight distinct sources of network uncertainty.[2] Four sources emerged that related to respondents meeting their partners' network. First people were uncertainty about being *approved* of, or *liked* by, their partner's network. People also were concerned about being *negatively judged* (e.g., negative evaluation, talking behind their back, holding their insecurities against them), or

[2] In this study, the authors asked participants about initial interactions with network members. The question was phrased as, "what uncertainties (if any) do you have about meeting one of your partner's network members whom you have not yet met?" This question was then reversed to describe uncertainties that participants had about introducing their partners to their own networks.

that someone from their partner's network would negatively influence the development of their relationship through infidelity or the encouragement of relationship-aversive behaviors (i.e., *third party threat*).

Second, four sources of uncertainty referred to respondents' partners meeting their network members emerged in Study 1. Participants described concerns of their network *approving* or *liking* their partner. Respondents also reported concerns that their partners might be *unjustifiably jealous* of one or more network members. Note that this source of uncertainty concerns both a partner and additional network member(s). Uncertainties about irrational jealousy concern more than just the two members of a dyad by taking into account extra—dyadic parties. Moreover, although this source of uncertainty focuses on a partner's perceptions, the source of those perceptions is the social network (Stein & Mongeau, under review).

Finally, individuals also experience uncertainties concerning their ability to spend sufficient leisure time with their partner and/or network to make both happy (i.e., *time split*, Stein et al., 2017). Said differently, participants worried that they would be unable to successfully juggle network time and partner time. Again, this source of uncertainty involves not only the partner, but also the network. Previous research has explored the time split phenomenon (e.g., Felmlee, 2001) and found it to be a salient concern that people experience as their relationships progress. Thus, much in the way that the term relational uncertainty acts as a conceptual structure that contains three distinct variables, the term network uncertainty was first thought to function as a construct that addresses eight sources of uncertainty.

Measuring Network Uncertainty

Stein and Mongeau (under review) use the results of their first study to develop a measure of network uncertainty. An exploratory factor analysis (EFA) produced five distinct factors. Three factors concerned uncertainties that individuals had about interacting with their partners' networks. The first factor represented respondents' uncertainty concerning their partner's network accepting them (*acceptance of self*). This factor combined the themes of *liking* and *approval* uncovered during qualitative analyses. Second, respondents worried that their partner's network might *negatively judge* them. Third, respondents were uncertain about potential *third party threat* (such as unwanted emotional or physical relationships between the partner and a network member). These last two factors represented distinct sources in Stein and Mongeau's Study 1.

When it came to respondents' concerns about their own network members interacting with their partners, two uncertainties emerged. Participants were worried about the extent to which their network would accept their partner (*acceptance of partner*). Sources of *liking* and *approval* were combined in this factor, suggesting that the two subscales work in tandem to generate uncertainties of acceptance. Stein and Mongeau (under review) argue that this dimension reduction is likely due to the close relationship between liking and approval during initial interaction (Berger & Calabrese, 1975). Second, participants were unsure of the degree to which their partners would display *unjustified jealousy* toward their own network members (e.g., fear that an innocent relationship was not so innocent). Importantly, *time split* items factored together with *unjustified jealousy* items. Thus, although partner jealousy and time split are conceptually distinct, they are empirically similar.

One final note concerns the amount of items used to measure network uncertainty. The initial measurement contained 40 items—five items for each of the eight original sources of uncertainty. Such a large measure is difficult to implement in survey research. What is more, lengthy measurements often cause difficulties for statistical techniques and conceptual arguments (Fodor, 2002). Stein and colleagues (2017) were able to reduce the measurement down to 18 items while still retaining the five factors and not sacrificing explained variation. The final factor structure of network uncertainty can be seen in Figure 2.

Source of Network Uncertainty	Description
Acceptance (from the partner's network)	Concerns about being liked or approved of by a partner's network member(s)
Judging (from the partners network)	Concerns about being judged by a partner's network member(s)
Third party threat (from the partner's network)	Concerns that a partner has a sexual or emotional attachment toward one or more of his/her network members
Acceptance (from one's own network)	Concerns that one's own network will not like or approve his/her partner
Jealously/time split (from one's own network)	Concerns that one will not be able to properly juggle free time spent with partner vs. network, resulting in jealousy from one or both parties.

Figure 2. – Sources of network uncertainty. These five distinct sources are dimensions of network uncertainty gleaned from an exploratory factor analysis of 18 measured items. The term *network uncertainty* is a global evaluation, whereas the sources listed in this figure are measured factors that index unique sources of uncertainty.

Network and Relational Uncertainty

A follow-up study to Stein and Mongeau (under review) sought to further investigate the network uncertainty measure (Stein et al., 2017). This study utilized confirmatory factor analysis (CFA) and path analysis to determine potential relationships between network uncertainty and relational uncertainty. It was predicted that the sources of uncertainty that pertained to a person interacting with their partner's network would form a second-order unidimensional factor structure. Additionally, sources of uncertainty pertaining to a partner interacting with the respondent's network were also predicted to factor on to a separate second-order variable. Finally, it was hypothesized that the two second-order factors would comprise a third-order unidimensional latent variable.

The logic behind these hypotheses stemmed from the nature of relational uncertainty. Specifically, self, partner, and relationship uncertainty are three measured variables that make up the construct of relational uncertainty (Knobloch & Solomon, 1999). On the other hand, as relationships blossom, networks overlap (Agnew et al., 2001; Sprecher & Felmlee, 2000), and are often considered as one source of influence by romantic partners (Sprecher, 2011). Thus, although the self, partner, and relationship constitute unique sources of uncertainty, the networks surrounding that relationship should account for a distinct source of uncertainty that ultimately shifts relational cognitions and behaviors.

The second goal of Stein et al.'s (2017) study was to initially test the relationship between network uncertainty and relational uncertainty. Because both self and partner uncertainty are determinants of relationship uncertainty (Solomon et al., 2016), there were at least three ways that network uncertainty would fit into such a model. The first was a model that depicted network uncertainty as a unique predictor of relationship uncertainty alongside self and partner uncertainty (i.e., a direct relationship between network uncertainty and relationship uncertainty). The second model depicts self and partner uncertainty fully mediating the association between network uncertainty and relationship uncertainty. The third model is a scenario in which self and partner uncertainty partially mediate the relationship between network uncertainty and relationship uncertainty. In this last model, network uncertainty is related to relationship uncertainty both directly and indirectly.

Results of the Stein et al. (2017) investigation were quite telling. First, as expected, second order factors emerged, such that acceptance of self, judging, and extra-dyadic interference composed a second-order factor. Acceptance of partner, unjustified jealousy/time split composed a second-order latent variable as well (Stein et al., 2017). Second, as predicted, a third order unidimensional variable emerged that encompassed all measured items (labeled *network uncertainty*). This finding is important for two reasons. First, it suggests a new factor structure of network uncertainty and its five distinct subscales. Second, it allows for a conceptual discussion of network uncertainty as a single entity (e.g., network uncertainty may lead to negative evaluations), as opposed to discussing the five subscales individually. One goal of this dissertation is to explore which measure(s) of network uncertainty (if any) explains the greatest amount of variation in self, partner, and relationship uncertainty. These findings may allow for a more parsimonious discussion of network uncertainty and potentially alter future measurements of the construct.

In addition, path analyses performed by Stein et al. (2017) revealed that the third-order factor (uncovered during CFA) is significantly and positively related to self, partner, and relationship uncertainty. The specifics of these relationships, however, are not yet definite. Stein and colleagues (2017) tested three different models to attempt to test direct, fully mediated, and partially mediated relationships between network and relational uncertainty. Results indicated that both the direct and indirect models fit the data equally well; however, regression weights were stronger for the model that positioned self and partner uncertainty as partial mediators of the association between network and relationship uncertainty. Given that this was a preliminary test of these relationships, how network uncertainty relates to relational uncertainty (self, partner and relationship) is still not completely clear.

There are three possible outcomes as it pertains to the associations between network uncertainty and relational uncertainty. First, it may be that network uncertainty is a fourth element of relational uncertainty. If this is the case two scenarios must be examined. On one hand, (sources of) network uncertainty might share a direct relationship with relationship uncertainty. On the other hand, it may be that self and/or partner uncertainty mediate the relationship between (sources of) network uncertainty and relationship uncertainty. The bootstrapping method of mediation (Preacher & Hayes, 2008) can test for these effects by exploring both direct and indirect effects between a predictor and outcome variable while controlling for mediating variables.

Second, it may be that network uncertainty is an antecedent to relational uncertainty, such that network uncertainty predicts self and/or partner uncertainty, which in turn predict relational uncertainty. If this is the case it suggests that network perceptions may influence dyadic perceptions more than RTT assumes. Parks and colleagues (1983) have demonstrated that network perceptions can lead to relational reevaluations. Moreover, Sprecher and Felmlee (1992, 2000) have shown that evaluations of network acceptance and support directly relate to feelings of love, intimacy, and closeness. If network uncertainty antecedes self and partner uncertainty it is another example of how network perceptions relates to dyadic perceptions.

Finally, it is possible that network uncertainty influences relational outcomes (e.g., biased cognitions; Solomon et al., 2016) above and beyond self, partner, and relationship uncertainty. Said differently it may be that network uncertainty is related to both relational uncertainty and the outcomes of relational uncertainty simultaneously. If this is the case, both direct and indirect effects of network uncertainty on biased outcomes should be tested for. Using the bootstrapping method of mediation testing (Preacher & Hayes, 2008), the direct effect of network uncertainty can be tested on measurements of biased cognitions. Additionally, indirect effects of network uncertainty can be tested on measured biased cognitions using self, partner, and/or relationship uncertainty as mediating variables. Uncovering the role of network uncertainty vis-à-vis relational uncertainty and biased cognitions is a primary goal of this dissertation.

Network Interdependence and Negative Emotions.

The second generative mechanism in RTT is partner interdependence (i.e., interference and facilitation; Solomon et al., 2016). Social networks share interdependent attributes (Surra, 1988); however, measurements of network interdependence were lacking. Thus, a third project (Stein, 2017) has explored the conceptual and empirical nature of network interdependence (specifically, interference and facilitation as measures of network influence).

It should be noted that whereas the conceptualization of network uncertainty emulated that of Knobloch and Solomon (1999), the conceptualization of network interdependence runs perpendicular to Surra's (1988) characterization of network interdependence. The notion of network interdependence, for this dissertation, stems from the conceptualization derived by Berscheid (1983) and measured by Knobloch and Solomon (2004) – that people both interfere with and facilitate each others' causal interchains. In other words, rather than measuring network interdependence as it is characterized by Surra, Stein's (2017) project sought to use Solomon and Knobloch's existing measurement of influence as a way of quantifying the already existing concept of network interdependence – bringing the two avenues of thought together.

In line with previous conceptualizations of interdependence (Berscheid, 1983; Knobloch & Solomon, 2004), *network influence* can be understood as "the degree to which a person's social network members help or hinder his/her everyday goals" (p. 9). Specifically, Stein (2017) defines *network interference* as the extent to which a person's network disrupts the romantic partners' daily goals and routine. Second, *network facilitation* is the extent to which a person's network helps partners accomplishing everyday goals.

Stein (2017) measured network interference and facilitation perceptions by modifying Knobloch and Solomon's (2004) existing scale of partner interference and facilitation, such that items that indexed the degree to which a partner influenced daily goals was changed to the degree to which network members influence every day goals. As previously noted, social networks both attempt to (Sprecher, 2011) and succeed in (Agnew et al., 2001; Felmlee, 2001) influencing relational outcomes. The results of Stein's study demonstrate some of the ways in which people perceive that their social networks influence their daily and relational goals.

Using EFA, unique measures of network interference and facilitation were developed. Analyses indicated that five items measured network interference, and five items tapped network facilitation (Stein, 2017). Each subscale was in line with the factors established by Knobloch and Solomon (2004). Following this initial measurement, CFA was run in order to test the goodness of fit for these measurements. Additionally, the study sought to see how (if at all) network interference/facilitation covary with partner interference/facilitation. Measurement models revealed excellent model fit on all accounts, such that network interference, network facilitation, partner interference, and partner facilitation all measure distinct subscales, but do not comprise a second (or third) order unidimensional variable (Stein, 2017). Importantly, no tests of construct validity were run in this manuscript. Thus, it remains unclear how, if at all, network interference and facilitation function as measured variables.

Summary, Hypotheses and Research Questions

The theoretical lens that best lends itself to the influence of network uncertainty and network interdependence is RTT. Although this dissertation does not test the tenets of RTT as a whole, the, primary goal is to explore the ways in which network-based variables (i.e., uncertainty and interdependence) relate to RTT processes. Specifically, this study will focus, for the most part, on the left-hand panel of Figure 1. Specifically, self, partner, and relationship uncertainty are predicted to lead to biased cognitions. In the present study, the biased cognition that will be investigated as the extent to which participants perceive that relational talk is threatening. Similarly, in RTT, partner interference and facilitation are predicted to predict intensified emotions (either positive or negative, depending on context). In this study, intensified emotions will include measures of anger, sadness, and fear when considering one's relationship. What is more, frequency of relationship-focused talk will be the measure that plays the role of communicative enactment. Finally, communicative valence will be measured by indications of the affective (i.e., positivity/negativity) nature of relational talk. A description of the relationships between network variables and turbulence variables follows.

Network Uncertainty Tests of Convergent and Divergent Validity

Stein and Mongeau's (under review) study demonstrated a strong positive relationship between the five sources of network uncertainty and the three elements of relational uncertainty. Stein and colleagues (2017) echoed these findings in their path analyses. Thus, at the bivariate level, measurements of network uncertainty should share a positive association with self, partner, and relationship uncertainty. This initial hypothesis is formally stated below.

> H1a: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will correlate positively with self uncertainty.

> H1b: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will correlate positively with partner uncertainty.

> H1c: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will correlate positively with relationship uncertainty.

In addition, network uncertainty may relate to measurements of partner interference and facilitation. Although not proposed by Figure 1 specifically, there is ample evidence to suggest correlations between these variables. Parks and colleagues (1983) demonstrated that perceptions of network support and approval are positively associated with romantic involvement – conceptualized as emotional attachment and frequency of interaction. Interdependence (as described by Berscheid, 1983) concerns the ways in which interaction with a partner impacts a person's daily routine and goals

(Knobloch & Solomon, 2004). Uncertainties about the ways in which one's own (or a partner's) network accepts and facilitate his/her relationship may result in decreased interaction within that relationship (due to an inability to manage daily goals and appropriately juggle network and partner time; Felmlee, 2001). What is more, self, partner, and relationship uncertainty all correlate positively with partner interference and negatively with partner facilitation at the bivariate level (Knobloch & Solomon, 2004). Thus, partner interference and facilitation should share positive and negative (respectfully) associations with network uncertainty items.

> H2a: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will correlate positively with partner interference
>
> H2b: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will negatively correlate with partner facilitation.

As RTT progresses through the first panel of Figure 1, a positive association between relational uncertainty and biased cognitions is specified (Solomon et al., 2016). One example of this relationship is that both self and relationship uncertainty positively indicate perceptions of relational talk as threatening (Theiss & Nagy, 2013). So too should there be a positive relationship between measurements network uncertainty and measurements of perceptions that relational talk is threatening. Lastly, although not specifically proposed by RTT, it has been demonstrated that heightened feelings of relational uncertainty can spark negative emotional reactions (Knobloch, Miller, &

Carpenter, 2007; Knobloch & Theiss, 2010). It is thus reasonable to question a positive relationship between network uncertainty and negative emotion.

H3: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will positively relate to items indexing the perception that relationship talk is threatening.

H4: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will positively relate to items indexing negative emotion.

One of the key elements of RTT is the enactment and valence of communication episodes (Solomon et al., 2016). In RTT, relationship uncertainty shares an indirect relationship with the enactment and valence of communication (through biased cognitive perceptions, see Figure 1). Typically, experiences of uncertainty negatively relate to both frequency of communication (Berger & Calabrese, 1975; Solomon & Knobloch, 2004) and the valence of communicative episodes (Berscheid, 1983; Knobloch & Satterlee, 2009). As such, measurements of network uncertainty are likely negatively related to both enactment of relational talk, and the valence of relational talk.

H5a: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will negatively relate to items indexing enactment of relational talk.

H5b: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will negatively relate to items indexing valence of relational talk.

One important unexplored relationship is between that of network uncertainty (Stein & Mongeau, under review) and network interdependence (Stein, 2017). Network uncertainty concerns the confidence that people have in their (and their partners') networks' acceptance and support. Such uncertainties (or their reductions) may relate to perceptions of network helpfulness and hindrance (as is the case for relational uncertainty; Knobloch Y& Donovan-Kicken, 2006). Tests of the relational turbulence mode have demonstrated negative correlations for self, partner, and relationship uncertainty with both partner interference and partner facilitation (e.g., Knobloch et al., 2007; Solomon & Theiss, 2008). Unlike relational uncertainty, however, network uncertainty may stem from concerns that the network is interfering with partner time (Felmlee, 2001). Thus, whereas network uncertainty should share a positive association with perceptions of network interference, it should share a negative relationship with network facilitation.

H6a: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will positively correlate with network interference.

H6a: Measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) will correlate negatively to network facilitation.

Concurrent Validity of Network Uncertainty

In order to properly test the theoretical viability of network uncertainty measurements, additional analyses will need to be performed aside from bivariate correlations. Specifically, structural equation modeling (SEM) will be used to test the concurrent validity of network uncertainty (and its sources). Below is a description of the hypotheses that will test how, if at all, network uncertainty can be used in RTT.

Increased interaction and familiarity with another person is argued to reduce uncertainty, both globally and relationally (although not necessarily in a positive way; Berger & Calabrese, 1975; Knobloch & Solomon, 1999). Moreover, reductions of relational uncertainty can increase both intimacy (Solomon & Theiss, 2008) and relationship satisfaction (Knobloch & Theiss, 2011). Along a similar lines, increasing partners' network overlap (i.e., familiarity with both partners' friends) generates these same outcomes (i.e., increased intimacy and satisfaction; Agnew et al., 2001). Therefore, it is proposed that network overlap provides the conditions by which an individual is less likely to experience network uncertainty. In particular, network overlap should reduce uncertainty about Partner A interacting with Partner B's network (or vice versa). In other words, network overlap should negatively relate to experiences of network uncertainty. For this study, network overlap is treated as a control variable; however, the nature of the relationship between network overlap and network uncertainty is worth discussing and is formally stated below.

H7: Network overlap will negatively relate to measures of network uncertainty.

Stein et al. (2017) indicated that network uncertainty is closely related to self, partner, and relationship uncertainty. The exact nature of these relationships, however, is yet to be determined, primarily because Stein and colleagues showed a minimal difference between their direct model and indirect models. It may be that network uncertainty is directly related to relationship uncertainty. On the other hand, it may be that self and/or partner uncertainty mediate the relationship between network uncertainty and relationship uncertainty.

In order to test how network uncertainty relates to relational uncertainty, several different effects should be tested. First, a hierarchical model will test the extent to which network uncertainty influences relationship uncertainty (along with self and partner uncertainty). In this first model, self, partner, and network uncertainty are positioned as predictor variables, whereas relationship uncertainty is position as an outcome variable. Preacher and Hayes (2008) describe this as the total effect of network uncertainty on relationship uncertainty. Second, the direct effect of network uncertainty on relationship uncertainty will be tested. This test allows for the testing of the unique effect of network uncertainty on relationship uncertainty while controlling for self and partner uncertainty. Finally, the indirect relationship between network and relationship uncertainty will be tested, using both self and partner uncertainty as mediators. In this instance, the effect of network uncertainty on relationship uncertainty through both self and partner uncertainty will be tested.

The expectation is that network uncertainty will influence relationship uncertainty in some way (either directly or indirectly). Because there are several ways that these relationships might occur, the associations are presented as a research question rather than a specific hypothesis. The relationship between network and relational uncertainty is articulated below.

RQ1: Is the relationship between measures of network uncertainty (network-to-self acceptance, judging, third part threat, network-to-partner acceptance, and jealousy/time split) and relational (self, partner, and relationship) uncertainty direct, partially mediated or fully mediated?

Extant work has demonstrated the relationships between self, partner and relationship uncertainty (e.g., Theiss & Solomon, 2006a; Theiss & Nagy, 2013). What is more, RTT (i.e., Figure 1) proposes that self and partner uncertainty both positively predict relationship uncertainty (Solomon et al., 2016). The present study allows for the replication of this prediction, stated below.

H8a: Self uncertainty is positively associated with relationship uncertainty

H8b: Partner uncertainty is positively associated with relationship uncertainty

According to RTT relational uncertainty should spark cognitive biases. Specifically, the theory predicts that relationship uncertainty mediates the relationship between self/partner uncertainty and biased cognitions. The perception that relational talk is threatening is the biased cognitive appraisal (Theiss & Nagy, 2013) that will be used in this study. Relational uncertainty should positively contribute to perceptions of relational talk as threatening. Specifically, relationship uncertainty should partially mediate the relationship between self uncertainty and perceptions of relational talk as threatening, while fully mediating the relationship between partner uncertainty and perceptions of relational talk as threatening (see Figure 1; Theiss & Nagy, 2013).

H9a: Relationship uncertainty will positively relate to the perception that relational talk is threatening.

H9b: Relationship uncertainty will partly mediate the association between self uncertainty and the perception that relationship talk is threatening.

H9c: Relationship uncertainty will fully mediate the association between partner uncertainty and the perception that relationship talk is threatening.

A final goal of this area of inquiry will be to see how measurements of network uncertainty influence the outcomes stipulated in RTT when controlling for self, partner, and relationship uncertainty. According to RTT (Solomon et al., 2016), self and relationship uncertainty are direct indicators of biased cognitions (e.g., perceptions that relational talk is threatening), whereas partner uncertainty is an indirect determinant of biased cognitions. Although previous work has demonstrated a close link between network uncertainty and relational uncertainty (Stein et al., 2017), it is not yet clear how measurements of network uncertainty relate to relational outcomes when controlling for self, partner, and relationship uncertainty. A research question addresses this potential relationship.

RQ2: What is the nature of the relationship between network uncertainty and the perception that relational talk is threatening, when controlling for self, partner, and relationship uncertainty?

Network Interdependence Tests of Convergent and Divergent Validity

A second goal of this dissertation is probe the newly developed measurement of network interdependence (i.e., network interference and facilitation; Stein, 2017). Consistent with Berscheid's (1983) description of interdependence, multiple people can simultaneously hinder and/or help with someone's everyday goal structures. It has been demonstrated that perceptions of network involvement (e.g., interfering and facilitating behaviors) positively influence perceptions of relationship involvement (Parks et al., 1983). Sprecher (2011) also showed that perceptions of network approval positively relate to facilitating behaviors from a partner. Felmlee (2001) demonstrated that perceptions of network support positively correlate with relational longevity. Given that interdependence is a key factor in relational development (Berscheid, 1983), perceptions of network interdependence should be significantly associated with perceptions of partner interdependence. Specifically, Knobloch and Solomon (2001) showed that, at the bivariate level, interference and facilitation are positively correlated. Thus, in the case of interference and facilitation, network variables should correlate with dyadic variables.

H10a: Items designed to measure network interference will positively correlate with items that index partner interference and partner facilitation.

H10b: Items designed to measure network facilitation will positively correlate with items that index partner interference and partner facilitation.

In addition to correlating with indicators of partner interference and facilitation, measures of network interference and facilitation should also correlate with other relational turbulence variables—assuming the scale is valid. In RTT, partner interference is predicted to spark negative emotions, whereas partner facilitation mitigates such experiences (Knobloch & Theiss, 2010; Solomon et al., 2016). As Berscheid (1983) describes, interdependence greatly contributes to emotional reactions in close relationships. Moreover, Stein (2017) made use of Berscheid's conceptual definition as well as Knobloch and Solomon's (2004) measure when crafting scales of network interference and facilitation. As such, while empirically distinct, network interdependence and partner interdependence likely correlate similarly with potential outcome variables. It is thus proposed that like partner interference and facilitation, network interference and facilitation will correlate significantly with measures of negative emotion, although in opposite directions.

H11a: Items measuring network interference are positively associated with items that index negative emotions.

H11b: Items measuring network facilitation are negatively associated with items that index negative emotions.

On a related note, it may be that perceptions of network interference and facilitation correlate with biased cognitions. Again, while not specified by RTT (see Figure 1), tests of the turbulence model have detailed an inverse relationship between partner interference and relationship inferences, such as perceived intimacy (Knobloch, 2007) and relationship satisfaction (Knobloch & Theiss, 2011). What is more, perceived interference from network members is inversely associated with relational assessments (e.g., perceptions of commitment and trust; Sinclair et al., 2014). On the other hand, facilitation often shares a positive correlation with relational assessments (e.g., Knobloch & Donovan-Kicken, 2006; Knobloch et al., 2007). It is therefore reasonable to suggest significant correlations between measures of network interdependence and the perception that relational talk is threatening. Thus, two hypotheses detail the potential association between measures of network interdependence and biased cognitions (in this case, the perception that relational talk is threatening).

H12a: Items measuring network interference are positively associated with items that index the perception that relational talk is threatening.

H12b: Items measuring network facilitation are negatively associated with items that index the perception that relational talk is threatening.

Concurrent Validity of Network Interdependence

One of the most important tests of a newly developed scale is that of its ability to relate to variables within theoretical suppositions (Worthington & Whittaker, 2006). In the case of network interdependence, the ability to predict negative emotional responses (as outlined in RTT; Solomon et al., 2016) is a key indicator of the scales' validity. Thus, the final goal of this dissertation will be to test if network interdependence is an indicator of negative emotion when controlling for partner interference and facilitation. Such a query must be tested with methods more robust than simple bivariate correlations – in this case SEM will be used to explore how, if at all network interdependence relates to negative emotions above and beyond partner interdependence. This test will help determine whether or not measures of network interference and facilitation are useful for theory development.

Like network uncertainty, the association between network interdependence, partner interdependence, and negative emotions is not yet specified and will thus be tested using three distinct models. The first model will test direct relationships, such that paths will be drawn from network interference, network facilitation, partner interference and partner facilitation (all distinct predictor variables) to negative emotions (the outcome variable). This test will allow for a test of the linear relationship between network interdependence and negative emotion while controlling for partner interdependence. The second test will explore fully mediated relationships, such that paths will be drawn from network interference and facilitation to partner interference and facilitation, and then from partner interference and facilitation to negative emotion. The final test considers partial mediation, such that both direct and indirect associations between network interdependence and negative emotion (through partner interdependence) will be investigated. Because none of these relationships have been tested, two research questions address all potential relationships described in this section.

RQ3a: Does network interference will influence levels of negative emotion when controlling for interference and facilitation?

RQ3b: Does network facilitation influence levels of negative emotion when controlling for partner interference and facilitation?

Chapter 2

METHOD

Participants and Procedure

After approval from the university's institutional review board, data were collected from 642 adult individuals across the United States. Participants were recruited through Amazon's *Mechanical Turk* (i.e., MTurk) to complete a survey about relationships and turbulence. Mechanical Turk was chosen for this study because previous work has demonstrated that MTurk samples are more diverse in terms of both ethnicity and age than convenience based samples (such as college students; Paolacci & Chandler, 2014). Additionally, MTurk samples have shown a higher level of reliability in terms of both response rate and mortality rate than convenience samples (Peer, Vosgerau, & Acquisti, 2014). Most importantly, the reliability and quality of data collected from MTurk samples do not statistically differ from college-aged samples (Buhrmester, Kwang, & Gosling, 2011). Respondents received $1.50 completing the survey. Researchers have indicated that cash rewards aid in both the participation rate and quality of completed surveys (Church, 1993; Singer, Van Hoewyk, Gebler, Raghunathan, McGonagle, 1999).

After providing consent, participants were sent through a screening procedure designed to ensure that they met qualifications. Qualifications included that participants be at least 18 years of age, have Internet access, and be currently in a romantic and/or sexual relationship of some kind at the time of data collection. Following qualification, respondents were guided through a series of Likert-style questions aimed to measure each of the variables of interest.

The present sample included approximated equal proportions of men (*n* = 336) and women (*n* = 306). Participants' age varied widely, ranging from 18–76 (*M* = 35.17, *SD* = 10.01). Participants, on average, had been in their relationships for 6.28 years (SD = 4.44). What is more, although the overwhelming majority of participants identified as heterosexual (*n* = 573), a number of participants identified as bisexual (*n* = 53) and homosexual (*n* = 16). People most commonly identified as being married (or in a civil union; *n* = 343) or in a serious dating relationship (*n* = 177). Less common relationship types included casual daters (*n* = 67) and engaged to be married (*n* = 55). The ethnicity of the sample was predominantly Caucasian (*n* = 409), followed by Asian (*n* = 113), Indian (*n* = 51), African American (*n* = 40) and Hispanic/Latino (*n* = 18). Seven individuals reported as being "mixed race," and there were two Native Americans and two Pacific Islanders in the sample.

Measurement and Instrumentation

In the present study nine different scales were used to collect data. Full descriptions of each scale (including scale items and prompts leading to each question) can be viewed in Appendix A. Means and standard deviations of all variables can be viewed in Table 1.

Network Overlap

To measure network overlap, a scale of relational closeness (Aron, Aron, & Smollan, 1992) was modified to reflect perceptions of network inclusion. This measure includes seven Venn diagrams that vary in how two circles overlap, ranging from not-touching to nearly completely overlapping. In the illustrations, one circle indicates the respondent's network, and the other circle represents their partner's network. As an alternative measure, participants were also asked to indicate the percentage to which they believe their networks overlap, where 0% indicates that neither partner is familiar with any of each other's network members and 100% indicates that both networks are completely overlapped such that everyone from both networks know each other at the personal level. During analysis, these two measurements were standardized and combined to represent a composite measure of network overlap (measures correlated at $r = .76$).

Network Uncertainty

Network uncertainty was measured using the scale developed by Stein and Mongeau (under review). The scale is composed of 18 Likert-style questions to indicate, "*how certain are you…*" about a number of prompts (e.g., that my partner's network approves of me; that my partner and my network get along). Subscales measuring network-to-self acceptance ($\alpha = .90$), judging ($\alpha = .90$), third party threat ($\alpha = .93$), network-to-partner acceptance ($\alpha = .91$), and jealousy/time split ($\alpha = .85$) were all deemed reliable. For these scales 1 = *completely or almost completely uncertain*, 7 = *completely or almost completely certain*. Items were coded such that higher scores indicated greater levels of uncertainty.

Relational Uncertainty

Relational uncertainty was measured using Knobloch and Solomon's (1999) scale. Participants were asked to respond to 19 Likert-style questions to indicate "*how certain are you…*" about a number of prompts designed to measure self, partner, and relationship uncertainty (e.g., that you are committed to your partner; that your partner loves you; that you want this relationship to work out in the long run). Specifically, six items measured self uncertainty (α = .90), six items measured partner uncertainty (α = .95), and seven items measured relationship uncertainty (α = .92). Each item was accompanied by scales ranging from 1 = *completely or almost completely uncertain*, 7 = *completely or almost completely certain*. Items were coded such that higher scores indicated greater levels of uncertainty.

Network Interdependence

Network interdependence scales resembled Knobloch and Solomon's (2004) partner influence scale; however, items were reworded to reflect the social network's (rather than the partner's) influence on daily goals and dyadic relationships, rather than assessing a partner's influence on goals and network relationships. Participants indicated their agreement with 15 items on a seven-interval Likert scale (e.g., my network makes it hard for me to complete my daily tasks; my social network helps me with my school/work). Subscales measuring network's *interference* (α = .94) and *facilitation* (α = .89) were all deemed reliable. For this scale, 1 = *strongly disagree* and 7 = *strongly agree*. High scores reflected greater levels of interference and facilitation.

Partner Interdependence

Knobloch and Solomon's (2004) partner influence scale assessed the interference and facilitation that individuals perceive receiving from their partners. Participants indicated their agreement with 15 items on a seven-interval Likert scale (e.g., this person makes it hard for me to complete my daily tasks; this person helps me with my school/work). Subscales measuring a partner's *interference* (α = .93) and *facilitation* (α = .89) were all deemed reliable. For this scale, 1 = *strongly disagree* and 7 = *strongly agree*. High scores will reflect greater levels of interdependence.

Perceptions of Relational Talk as Threatening

Knobloch and Carpenter-Theune's (2004) measure of perceived threat of relational talk was used in this study. Participants will respond to five 7-point Likert scale items indicating their agreement (1 = *strongly disagree*; 7 = *strongly agree*) with a series of statements following the prompt, "*having a conversation about the nature of this relationship would…*" a) threaten the relationship, b) be embarrassing for me, c) have a negative effect on the relationship, d) make me feel vulnerable, and e) damage the relationship. This measurement was found to be reliable (α = .93).

Negative Emotion

To measure negative emotion, Dillard, Kinney, and Cruz's (1996) *emotions in close relationships* scale was used. Participants indicated their agreement on a seven-point Likert scale (1 = *strongly disagree*; 7 = *strongly agree*) with nine prompts that assessed their emotional state when thinking about their current relationship (e.g., *at the present time*, *my relationship makes me feel*… "angry," "fearful," "dismal."). Despite being distinctly different emotions, all nine items factored into a single, unidimensional scale. This measurement was deemed reliable (α = .96).

Enacted Relational Talk

Knobloch and Theiss' (2011) scale of enacted relational talk was used for this study. Participants responded to three Likert-style items prompted by the statement, "During the past week, we have actively avoided or actively discussed..." (1 = *actively avoided*; 7 = *actively discussed*): a) our view of this relationship, b) our feelings for each other, and c) the future of the relationship. The measurement was deemed reliable (α = .88).

Valence of Relational Talk

The valence of relational talk was assessed using three follow-up questions for each relational talk prompt. This question was designed to gauge the positivity/negativity of each relational topic. Respondents will respond to three 7-point Likert-style questions to indicate the level of positivity of each relational topic by responding to the prompt "I believe that discussing (e.g., our feelings for each other) went…" (1 = *extremely negatively*; 7 = *extremely positively*). There was also an eighth option for those participants who had never discussed each of the three topics. Those who selected this option were removed from analysis. This measure was found to be reliable (α = .88).

Table 1

Means and Standard Deviations for All Measured Variables

Variable	*M*	*SD*	α
Acceptance of Self	2.21	1.19	.90
Judging	3.13	1.58	.90
Third Party Threat	1.93	1.47	.93
Acceptance of Partner	2.39	1.31	.91
Jealousy/time split	2.36	1.29	.85
Self uncertainty	1.88	1.03	.90
Partner uncertainty	2.98	1.32	.95
Relationship uncertainty	2.13	1.22	.92
Partner interference	2.98	1.77	.93
Partner facilitation	4.16	1.50	.89
Network interference	3.44	1.69	.93
Network facilitation	5.02	1.22	.89
Relationship talk as threatening	2.49	1.53	.93
Negative emotion	2.09	1.40	.96
Enacted relational talk	4.87	1.36	.88
Valence of relational talk	6.22	1.32	.88

Chapter Three

RESULTS

In order to conduct analyses using AMOS, participants with any more than two percent of answers missing at random were removed from the data set. This practice led to the removal of 134 respondents, leading to a final sample of 642 adult individuals. Mean imputation was used to replace random missing data when participants had less than two percent of missing data (Scheffer, 2002). Importantly, because of the large sample size in this dissertation, the critical alpha for all proposed hypotheses was adjusted to .01

Testing SEM Assumptions

Structural equation modeling assumes linearity, multicolinearity, and homoscedasticity (Hoyle, 2012). In order to check for linearity, curve estimates (i.e., regressions designed to test linear versus quadratic or cubic relationships) were performed. For these estimates, model summaries report a series of equations including linear, quadratic, cubic, compound, and growth relationships. In a linear relationship, the omnibus ANOVA should meet two criteria. First, The F value for linear relationships should be significant at the critical alpha of .01. Second, the F value for linear relationships should be larger (ideally) or marginally smaller (no less than half) of the F value for all other tested relationships (Gefen, Straub, & Boudreau, 2000). These regressions are run for all hypothesized relationships. In all cases, relationships met both criteria indicating that were sufficiently linear for analysis. In other words, the relationships between all measured variables were linear.

Second, the assumption of multicolinearity must be tested. Briefly, a violation of multicolinearity occurs when two or more predictor variables are so highly correlated that they account for redundant variance in the dependence variable. In order to test for multicolinearity, a series of linear regressions were performed. These regressions are performed for all predictor variables that predict outcome variables in tandem (e.g., the proposal that self and partner uncertainty predict relationship uncertainty alongside one another). In these regressions, colinearity statistics are inspected. Specifically, variance inflation factor (i.e., VIF) scores of less than 3.0 indicate excellent tolerance and a VIF of less than 10.0 indicating adequate tolerance (Grewal, Cote, & Baumgartner, 2004). In the case of multicolinearity, *tolerance* refers to the degree to which predictor variables can be correlated without explaining redundant variance. In other words, it is acceptable if independent variables are correlated, as long as they do not explain largely overlapping variance in a dependent variable. For all independent variables, VIF values were less than 3.0 indicating that there are no redundancy issues.

Finally, the assumption of homoscedasticity proposes that the amount of error variation (and covariance) in dependent variables is the same across levels of the predictor variable. This assumption is ordinarily tested by running linear regressions between variables and observing the error between the estimated line of fit and the other plots (i.e., Bartlett's test of equal variances). Specifically, each proposed relationship (i.e., each proposed hypothesis) should be tested individually, observing any potential changes in error across the distribution of each independent variable. In other words, if error increases or decreases throughout the course of a distribution, that distribution is considered heteroscedastistic. Because the current model is being tested with multi-group mediators (Hoyle, 2012), heteroscedasticity is expected. As a result, this assumption was not tested. Moreover, the SEM is particularly robust in the face of violations of the homoscedasticity assumption (Gefen et al., 2000), in that correct estimates should be provided even if the assumption is violated. Thus, heteroscedastistic distributions are of little cause for concern.

Covariates and Controls

Potential controls for this study include network overlap, age, length of relationship, sex, ethnicity, sexuality, and relationship type. In order to observe a potential relationship between age/relationship length and measured variables in this study, a series of linear regressions were performed. Age and relationship length were predictor variables and all variables used in the study were outcome variables. All of the models explained a significant ($p < .01$), though relatively small amount of variation in study variables (R^2 ranged from .02 to .10). In all cases, relationship length (but not age) was a significant predictor. Thus, relationship length was controlled for in all substantive analyses.

In order to test for differences by sex, ethnicity, sexuality, and relationship type, a multivariate analysis of variance (MANOVA) was performed. For this test, main effects of all four grouping variables were tested for all of the study variables. At the multivariate level, results were nonsignificant for sex, $F(22, 1098) = 1.62$, Wilks' Λ□= .94, $p = .03$, ethnicity, $F(88, 3602) = 1.66$, Wilks' Λ□= .97, $p = .04$, and relationship type, $F(55, 2540) = 1.42$, Wilks' Λ□= .97, $p = .03$. Measurements of multivariate effect sizes were minimal. At the univariate level, effect sizes were marginal as well ($\eta^2 < .05$ in all cases). Scheffe post-hoc tests indicated no differences between subsets for any grouping variables. Thus, sex, ethnicity, sexuality, and relationship type were not controlled for when testing hypotheses.

Preliminary Analyses

Prior to path analysis, two preliminary analyses were performed to determine that variables met model-fit requirements for SEM (Gefen et al., 2000). First, EFA were conducted for each measure. This was done strictly as a formality to ensure that factor structure would turn out as predicted. During EFA, the three subscales measuring negative emotion (anger, sadness, and fear) loaded onto one factor, and were thus treated as such. Second, CFA were performed (i.e., measurement models) to ensure that all factors meet the appropriate goodness-of-fit criteria. A detailed description of this procedure is described below.

Confirmatory Factor Analysis

Confirmatory factor analysis was performed using AMOS/SPSS version 23 to test the measurement models for each variable used in substantive analyses. Multiple fit indices were implemented to test goodness of fit: the χ^2/df, with values under 5.0 indicating good fit and under 3.0 indicating excellent fit (Schumacker & Lomax, 2004); the comparative fit index (CFI) with values at or above .90 indicating adequate fit and .95 indicating excellent fit (Hu & Bentler, 1995, 1999); and the Root Mean Square Error of Approximation (RMSEA) with values under .10 indicating good fit and values under .06 indicating excellent fit (Browne & Cudek, 1993; Hu & Bentler, 1999).

The first model analyzed network uncertainty across the five dimensions revealed in previous investigations (acceptance of self, judging, third party threat, acceptance of partner, and jealousy/time split; Stein & Mongeau, under review). For this CFA, three models were tested. These three different models represent the three potential ways in which network uncertainty might be measured: as five first order factors, as two second order factors, and as one third order factor. Each of these measures has been tested in the past (see Stein et al., 2017); however, replication of these tests is necessary to test the external validity of the measures.

First, all five sources of network uncertainty were considered as distinct latent variables, each composed of a series of measured items. Second, a model including two second-order unidimensional factors was created. The *self's network uncertainty* second-order variable contained the latent variables acceptance of self, judging, and third party threat. The *other's network uncertainty* second-order variable consisted of acceptance of partner, and jealousy/time split. Finally, a third-order unidimensional variable was created (labeled *network uncertainty*) that was composed of the two second-order variables (i.e., self's network uncertainty and partner's network uncertainty). Third-order factors have been explored and often represent a more parsimonious measurement of latent variables (Rijmen, Jeon, von Davier, & Rabe-Hesketh, 2014).

The hierarchical model measuring network uncertainty as a third-order unidimensional variable bordered adequate fit, $\chi^2(125) = 720.0$; $\chi^2/df = 5.76$; CFI = .96; and RMSEA = .081. Modification indices indicated that adding covariation between error values (within each latent variable) would improve fit and were applied. For this scale, eight paths of covariation were added between errors. The resulting model indicated excellent fit for the third-order hierarchical model, $\chi^2(125) = 359.40$; $\chi^2/df = 2.88$; CFI = .97; and RMSEA = .054. Full results of this analysis can be viewed in Figure 3.

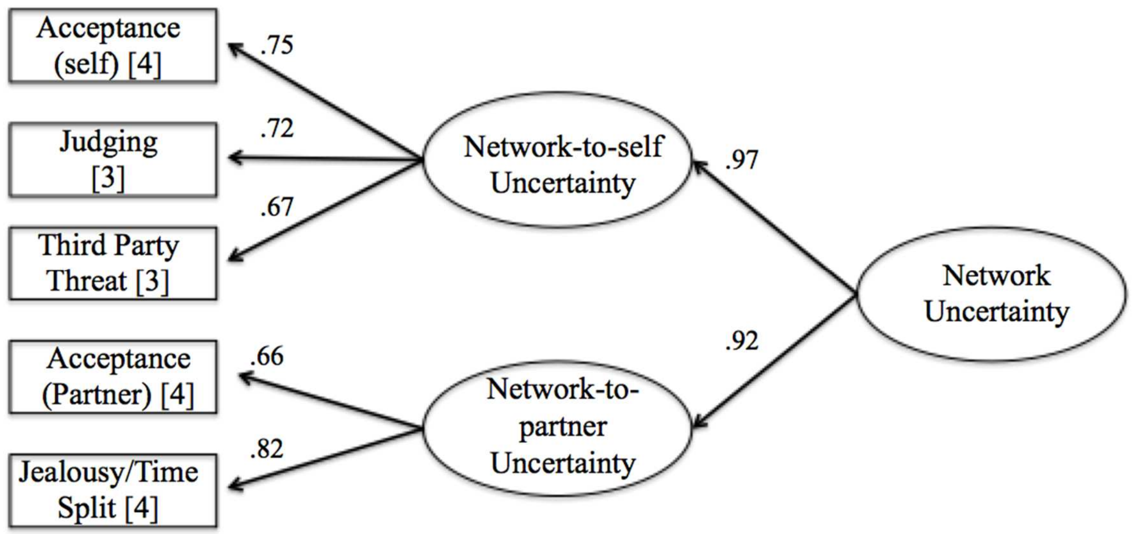

Figure 3. Confirmatory factor analysis for network uncertainty. $\chi^2(125) = 359.40$; $\chi^2/df = 2.88$; CFI = .97; and RMSEA = .054. Bracketed numbers represent the number of measured items used to measure each first-order factor.

Next, CFA models were created for self, partner, and relationship uncertainty as three distinct unidimensional latent variables. The initial model demonstrated poor fit, $\chi^2(86) = 473.86$; $\chi^2/df = 5.51$; CFI = .94; and RMSEA = .011. Modification indices were consulted and seven covariation paths were drawn between errors among measured variables that resulted in adequate model fit, $\chi^2(125) = 429.73$; $\chi^2/df = 4.99$; CFI = .96; and RMSEA = .079.

Next, measurements of network interdependence (*network interference* and *network facilitation*) were assessed. The initial measurement model demonstrated excellent model fit $\chi^2(30) = 63.28$; $\chi^2/df = 2.11$; CFI = .99; and RMSEA = .042.

Similarly, partner interdependence measurements (*partner interference, partner facilitation,* and *neutral partner influence*) were analyzed. The initial model demonstrated poor fir, $\chi^2(59) = 339.84$; $\chi^2/df = 5.76$; CFI = .94; and RMSEA = .086. After consulting modification indices, and drawing 2 paths of covariation between errors, the resulting model demonstrated adequate fit, $\chi^2(59) = 248.59$; $\chi^2/df = 4.21$; CFI = .96; and RMSEA = .077.

The model designed to measure perceptions of relational talk as threatening included only five items. Therefore, the model fit was excellent initially, $\chi^2(3) = 2.57$; $\chi^2/df = .86$; CFI = 1.0; and RMSEA < .001. These results are interpreted with caution due to the minimal number of measured items in this model.

Measurement models for negative emotion were conducted next. Because EFA results indicated that the emotions of sadness, anger, and fear all loaded on to one distinct factor, the hierarchical measurement model featured only one latent variable composed of nine items. The first model bordered on adequate fit, $\chi^2(15) = 104.25$; $\chi^2/df = 6.95$; CFI = .96; and RMSEA = .097. The modification indices suggested that one path of covariance between errors should be drawn to improve fit. The resulting model demonstrated good-to-excellent fit, $\chi^2(15) = 47.52$; $\chi^2/df = 3.17$; CFI = .99; and RMSEA = .058.

The model designed to measure perceptions of relational talk as threatening included five items, and the initial model fit was excellent, $\chi^2(3) = 2.57$; $\chi^2/df = .86$; CFI = 1.0; and RMSEA < .001. These results are interpreted with caution due to the small number of measured items in this model.

In sum, measurement models for all variables designed to measure turbulence markers, emotions, cognitions, and communication all demonstrated good fit after several iterations of CFA. It was thus deemed acceptable to perform path analysis using all of the variables included in this study.

Substantive Analyses

For both network uncertainty and network interdependence, tests of convergent and divergent validity were performed initially (using bivariate correlations), followed by test of concurrent validity (performed with SEM). Thus, this section contains four main subsections: convergent and divergent validity for network uncertainty, concurrent validity for network uncertainty, convergent and divergent validity for network interdependence, and concurrent validity of network interdependence.

Convergent and Divergent Validity of Network Uncertainty

To test the convergent and divergent validity of measurements of network uncertainty, subscales were correlated with RTT variables (Campell & Fiske, 1959). Specifically, it was predicted that measures of network uncertainty (network-to-self acceptance, judging, third party threat, network-to-partner acceptance, and jealousy/time split) would correlate positively with self (H1a), partner (H1b), and relationship (H1c) uncertainty. Measures of network uncertainty were also hypothesized to correlate positively with partner interference (H2a), perceptions that relational talks is threatening (H3), negative emotion (H4), and network interference (H6a). Conversely, network uncertainty measures were predicted to share negative relationships with partner facilitation (H2b), enacted relational talk (H5a), valence of relational talk (H5b), and network facilitation (H6b). The results of these associations are discussed below. Correlations between all variables can be viewed in Appendix B.

To test the first hypothesis (i.e., positive relationships between network and relational uncertainty), bivariate correlations were run between the five measures of network uncertainty and the three measures of relational uncertainty. As hypothesized, all

15 correlations were statically significant ($p < .01$) and positive (see Table 2). Briefly, four of the five sources of network uncertainty shared strong positive relationships with self, partner, and relationship uncertainty. Judging shared a moderate positive relationship with all three sources of relational uncertainty.

Table 2

Bivariate Correlations Between Sources of Network Uncertainty and Elements of Relational Uncertainty

Measures	Self Uncertainty	Partner Uncertainty	Relationship Uncertainty
1. Acceptance of Self	.53*	.51*	.54*
2. Judging	.28*	.34*	.38*
3. Third Party Threat	.53*	.52*	.52*
4. Acceptance of partner	.48*	.45*	.52*
5. Jealous/Time Split	.51*	.44*	.53*

Note. *$p < .01$.

Second, sources of network uncertainty were predicted to correlate positively with partner interference and negatively with partner facilitation (H2). Nine of ten correlations were significant and in the predicted direction (see Table 3). The only nonsignificant relationship was between judging and partner interference. These results largely support for H2.

Table 3

Bivariate Correlations Between Sources of Network Uncertainty and Elements of Partner Interdependence

Measures	Partner Interference	Partner Facilitation
1. Acceptance of Self	.15*	-.36*
2. Judging	.09	-.41*
3. Third Party Threat	.29*	-.24*
4. Acceptance of partner	.18*	-.42*
5. Jealous/Time Split	.41*	-.35*

Note. *p < .01.

Positive correlations were also predicted for network uncertainty measures with the perception that relational talk is threatening (H3) and negative emotion (H4). Nine of ten correlations noted in these two hypotheses were significant and in the predicted direction (full results can be seen in Table 4). The only nonsignificant relationship was between judging and perceptions of relational talk as threatening. Thus, H3 received partial support, and H4 received full support.

Table 4

Bivariate Correlations Between Sources of Network Uncertainty, Perceptions of Relational Talk as Threatening, and Negative Emotion Concerning One's Relationship

Measures	Rel. Talk as Threatening	Negative Emotion
1. Acceptance of Self	.33*	.27*
2. Judging	.12	.13*
3. Third Party Threat	.37*	.37*
4. Acceptance of partner	.32*	.32*
5. Jealous/Time Split	.38*	.38*

Note. $^{*}p < .01$.

The fifth hypothesis (H5) predicted that network uncertainty would negatively correlate with the amount and valence of enacted relational talk. All 10 correlations were statistically significant and in the predicted direction (see Table 5). Both enacted relational talk and the valence of relational talk shared small-to-moderate negative relationships with measures of network uncertainty. These results provide full support for H5.

The sixth hypothesis (H6) argued that measures of network uncertainty would share a positive relationship with network interference and a negative relationship with network facilitation. Of the ten relevant correlations, five were significant and in the predicted direction. Neither judging nor acceptance of partner were significantly related to network interference. Conversely, neither acceptance of self, third party threat, nor jealousy/time split were related to partner interference. These results provide partial support for H6. See Table 6 for results of this hypothesis.

Table 5

Bivariate Correlations Between Sources of Network Uncertainty and the Enactment and Valence of Relational Talk

Measures	Enacted Relational Talk	Valence of Relational Talk
1. Acceptance of self	-.16*	-.24*
2. Judging	-.19*	-16*
3. Third Party Threat	-.13*	-.32*
4. Acceptance of Partner	-.24*	-.27*
5. Jealous/Time Split	-.16*	-.28*

Note. *$p < .01$.

Concurrent Validity: Testing Network Uncertainty Within RTT

Although bivariate correlations are important as initial indicators of validity, more complex analyses are necessary for determining the theoretical and heuristic usefulness of a scale (Worthington & Whittaker, 2006). Moreover, given RTT predictions are causal in nature, the role of network uncertainty can be tested with SEM to gauge associations between particular variables of interest while controlling for all other variables in a model (Hoyle, 2012).

Table 6

Bivariate Correlations Between Sources of Network Uncertainty and Elements of Network Interdependence

Measures	Network Interference	Network Facilitation
1. Acceptance of Self	.15*	-.10
2. Judging	.07	-.27*
3. Third Party Threat	.28*	.06
4. Acceptance of partner	.05	-.21*
5. Jealous/Time Split	.30*	.01

Note. *p < .01.

Tests of the role of network uncertainty in the first panel of RTT (see Figure 1) were performed using SPSS 23's AMOS (i.e., SEM). In this program, variables are created by physically drawing measured (represented with a rectangle) or latent (represented with an oval) variables. Hoyle (2012) discusses two distinct options for SEM. The first method involves creating composite variables (rectangles) composed of the items used to measure each variable. For example, because the five measured sources of network uncertainty are each represented by several measured items, composites for each factor would be created, and those averages would be used as a single measured variable in AMOS. This technique reduces the number of parameters involved in the analysis, potentially increasing model fit, but also limiting the nuance of variation between variables.

On the other hand, a series of latent variables could be drawn in place of measured variables. This method increases number of parameters involved, but also increases the degrees of freedom present during analysis, balancing out model fit and allowing for a more nuanced analysis. For this dissertation, the latter method was chosen for two reasons. First, as noted above, latent models capture more nuances than do measured models (Hoyle, 2012). Second, because of the already large number of variables in the present study, increasing degrees of freedom was ultimately necessary to meet model fit.

Hypotheses presented three separate instances of mediation that can be tested with SEM. First, RQ1 focused upon the extent to which self and partner uncertainty mediated the relationship between (measures of) network uncertainty and relationship uncertainty. Second, H9 predicted that relationship uncertainty mediates the relationship between self and partner uncertainty and the perception that relational talk is threatening. Third, RQ2 questions if self, partner, and/or relationship uncertainty mediate the relationship between (measures of) network uncertainty and the perception that relational talk is threatening.

In this project, mediation was tested for using Preacher and Hayes' (2008) bootstrapping method. In this method, three sets of paths are analyzed. First, the total path (i.e., a regression weight) from the predictor variable to the outcome variable (labeled path C) is assessed for significance. Second, the direct relationship between the predictor variable and outcome variable is observed while including the moderating variable (labeled path C'). Finally, the indirect path between the predictor and outcome variables, through the mediating variable, is tested (labeled path AB). This effect is the product of the relationship between the predictor and the mediator and the relationship between the mediator and the outcome variable. In order for partial mediation to occur, path C, path C' and path AB should all be significant. For full mediation, only path C and path AB should be significant. Preacher and Hayes explain that it is possible to test for multiple simultaneous mediators. However, due to the high intercorrelations between potential moderator variables (i.e., self, partner, and relationship uncertainty), the regression weights between moderator variables and outcome variables may be attenuated. Thus in these analyses, potential moderating variables are tested individually.

Network uncertainty and relational uncertainty. One of the primary goals of this project is to specify the relationship between sources of network uncertainty and sources of relational uncertainty. As can be seen in Figure 4, the exact associations between these variables are not yet known; however, prior research has indicated that a) network overlap is an inverse indicator of network uncertainty and b) measurements of network uncertainty share a strong, positive relationship with self, partner, and relationship uncertainty (Stein et al., 2017).

Two important questions remain, however, concerning the role that network uncertainty serves vis-à-vis relational uncertainty. The first question focuses on the dimensionality of network uncertainty. First, it is possible that one (or more) of the five measures of network uncertainty separately contribute(s) to self, partner, and relationship uncertainty. Second, the five sources of network uncertainty may combine to elicit self, partner and/or relationship uncertainty. Put differently, it may but that network uncertainty, as an independent variable, is made up of five distinct dimensions, or one unidimensional variable. Given the results of bivariate tests and CFA, it is possible that both models will fit the data. As such it is important to distinguish whether one model explains more variation in outcome variables than another. This is done by observing the summed squares of correlations (i.e., R^2) for each outcome variable. Put differently, the explained variance for each endogenous variable (as a result of predictor variable[s]) can be ascertained in SEM. It may be that the five distinct measures of network uncertainty explain more, less, or an equal amount of variance in endogenous variables, compared to a unidimensional measure of network uncertainty.

What is more, the effects of network uncertainty on relationship uncertainty may be either direct or indirect. It may by that network uncertainty (as one dimension or five) directly affects self, partner, and relationship uncertainty. It may also be that either self and/or partner uncertainty mediate the relationship (partially or fully) between network uncertainty and relationship uncertainty.

Two hypotheses and one research question focus on the relationships between network overlap, network uncertainty, and relational uncertainty. The seventh hypothesis predicted a negative relationship between perceptions of network overlap and network uncertainty (i.e., increases in network overlap should reduce network uncertainty). Moreover, RQ1 centered upon the association between network uncertainty and relational uncertainty. Finally, there was a positive relationship predicted between self (H8a) and partner (H8b) uncertainty with relationship uncertainty. These hypotheses and questions were examined together to best determine the interrelationships among network uncertainty and relational uncertainty, and are shown in Figure 4.

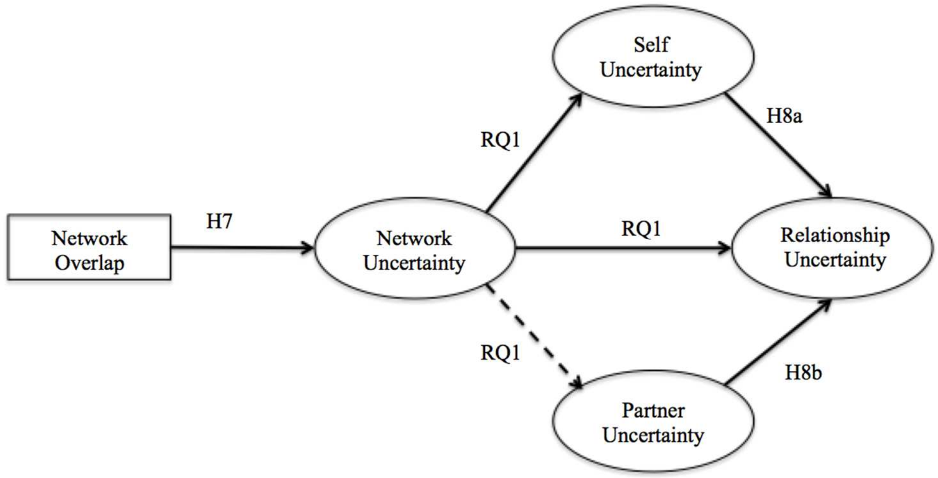

Figure 4. Hypothesized relationships between network overlap, network uncertainty, self, uncertainty, partner uncertainty, and relationship uncertainty. In this figure, *network uncertainty* is represented as a latent variable; however, tests of network uncertainty will be performed in two ways: first displaying network uncertainty as five distinct measured variables, and second displaying network uncertainty as a third-order unidimensional variable.

In order to simultaneously probe H7, H8, and RQ1, two path models were tested that differed in the dimensionality of the network uncertainty measure. First, based on the five-factor structure uncovered by Stein and Mongeau (2017), the individual sources of network uncertainty (acceptance of self, judging, third party threat, acceptance of partner, and jealousy/time split) were tested as distinct measured variables. This method was chosen for two reasons. First, this practice can allow an exploration of the unique relationships that each source of network uncertainty shares with self, partner, and relationship uncertainty. Second, it can determine if some elements of network uncertainty are stronger indicators of self, partner, and relationship than others, as bivariate correlations suggested.

In addition, the same predictions were tested using a unidimensional measurement model (revealed during CFA: network uncertainty as a third-order latent unidimensional variable) as a single predictor of self, partner, and relationship uncertainty. This second model is a less nuanced, but a more parsimonious, casual structure. Comparing the predictive ability of these two models (i.e., assessing the R^2 for endogenous variables in each model) will provide evidence to help decide whether network uncertainty is a five-dimensional, or a one-dimensional construct. Both models are tested below. Notably, the second-order variables (i.e., network-to-self uncertainty and network-to-partner uncertainty) are not reported in this dissertation due to the redundancy of the findings.[3] In short, the effects of the second-order variables provided no novel findings when compared to tests of network uncertainty as multidimensional or unidimensional.

Network uncertainty as multidimensional. In the first model, individual paths were drawn between all five measured elements of network uncertainty (acceptance of self, judging, third party threat, acceptance of partner, and jealousy/time split) and relational uncertainty components (self, partner, and relationship). Such a model allowed tests of self and partner uncertainty as mediators of the association between (measures of) network uncertainty and relationship uncertainty. Again, although the Preacher & Hayes (2008) mediation test allows tests of multiple mediators; however, the large intercorrelations between moderators (i.e., self and partner uncertainty), suggested separate models of analysis. One model considered self uncertainty as a mediating variable and the other considered partner uncertainty as a mediating variable. Finally, in all models, the variable network overlap is treated as a control variable in that it has paths drawn to network uncertainty (in this case as five separate factors).

[3] Path analyses were performed for the second-order factors network-to-self uncertainty and network-to-partner uncertainty Findings indicated partial mediation for both self and partner uncertainty; however, regression weights and R^2 were weaker than those of the third-order variable and were thus not included in the results.

Self uncertainty as a mediator. The first model used self uncertainty as a mediating variable between the five measures of network uncertainty and relationship uncertainty (see Figure 5 and Table 7). This model demonstrated acceptable fit,□$\chi^2(197) = 845.13$; $\chi^2/df = 4.29$; CFI = .93; and RMSEA = .081. First, the effects of network overlap on sources of network uncertainty were observed. Results demonstrated significant and negative relationships between network overlap and all five sources of network uncertainty (β raged from -.11 to -.31). This provides support for H7.

Next, regression weights for measures of network uncertainty and relationship uncertainty were assessed in terms of total, direct, and indirect effects. For the *total effects* results, acceptance of self (β = .10), acceptance of partner (β = .12), and jealous/time split (β = .13), were significantly and positively related to relationship uncertainty. Total effects for third party threat (β = .02) and judging (β = .02) on relationship uncertainty were not significant.

Next, *direct effects* of network uncertainty dimensions on relationship uncertainty were assessed. In this estimate, the direct effect of self uncertainty (the moderator) on relationship uncertainty is controlled for while observing the relationship between sources of network uncertainty and relationship uncertainty. When including for self uncertainty, only judging (β = .06) was significantly related to relationship uncertainty. No other sources of network uncertainty shared a significant association with relationship uncertainty while controlling for self uncertainty at the critical alpha of .01 (β < .03 in all cases).

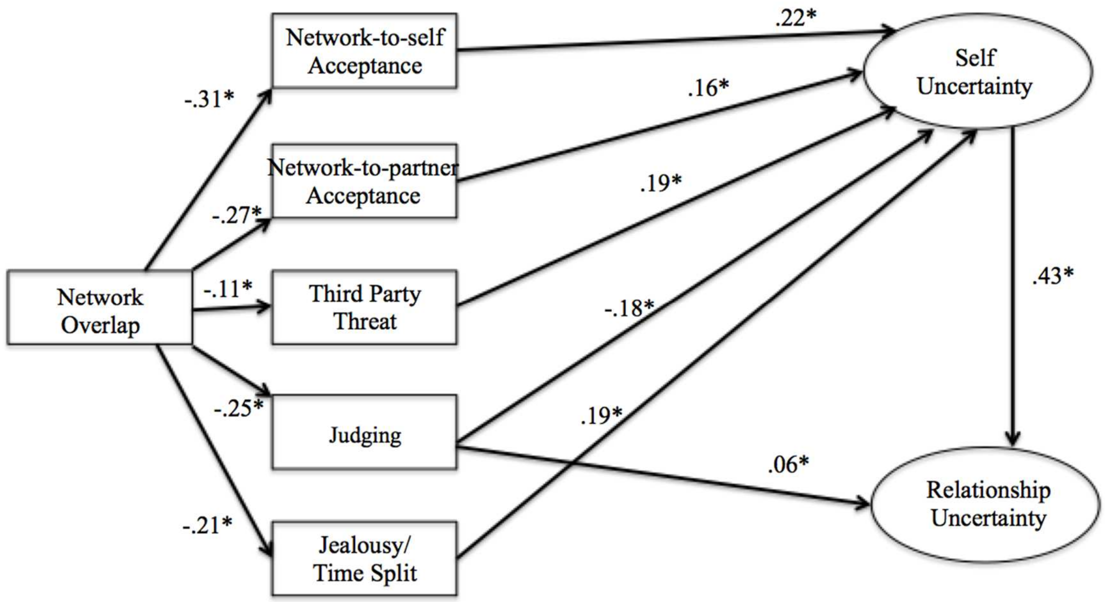

Figure 5. Associations between sources of network uncertainty and relationship uncertainty, mediated by self uncertainty. Only significant paths are shown in this model. All paths in this figure are standardized. For this model, $\chi^2(197) = 845.13$; $\chi^2/df = 4.29$; CFI = .93; and RMSEA = .081. *$p < .01$. Length of relationship is controlled for, but not shown in, this model.

Finally, to test the *indirect effects*, paths were drawn from all five measurements of network uncertainty to self uncertainty, and then from self uncertainty to relationship uncertainty. There was a significant indirect relationship for acceptance of self (β = .09), acceptance of partner (β = .07), and jealousy/time split (β = .08), judging (β = -.08), and third party threat (β = .07) on relationship uncertainty These results are a product of the direct effect of network uncertainty dimensions on self uncertainty and the direct effect of self uncertainty on relationship uncertainty. The five sources of network uncertainty explained approximated 36% of the variation in self uncertainty (i.e., R^2 = .36).

All five sources of network uncertainty were directly related to self uncertainty; however, it is notable that judging shared a negative relationship with self uncertainty (β□□□□□18□□ The five sources of network uncertainty explained approximated 41% of the variation in self uncertainty (i.e., $R^2 = .41$). Full results of mediation tests can be viewed in Table 7.

From these three tests it can be determined that self uncertainty serves as a full mediator of the relationships between acceptance of self, acceptance of partner, third party threat, and jealousy/time split and relationship uncertainty. Self uncertainty served as a partial mediator for the relationship between judging and relationship uncertainty; however, this estimate is likely due to a suppression effect. This is because the direct effect of jealousy is on relationship uncertainty positive, and the indirect effect (as well as the zero-order correlation) is negative. As such, the result should be interpreted with caution. Similarly, the indirect effect for *third party threat* may also be a suppression effect

Table 7

Effects of Sources of Network Uncertainty on Relationship Uncertainty, Mediated by Self Uncertainty

			Total effect		Direct effect		Indirect effect		95% CI	
IV	DV	MV	Est.	SE	Est.	SE	Est.	SE	Upper	Lower
AS	RU	SU	.13*	.026	.04	.028	.09*	.019	.166	.034
JU	RU	SU	.02	.018	.07*	.019	-.05*	.013	-.027	-.094
TpT	RU	SU	.02	.018	-.04	.020	.05*	.013	.102	.016
AP	RU	SU	.10*	.022	.04	.023	.06*	.016	.123	.013
JT	RU	SU	.11*	.023	.04	.025	.07*	.017	.142	.018

Note. AS = acceptance of self, JU = judging, TpT = third party threat, AP = acceptance of partner, JT = jealousy/time split, RU = relationship uncertainty, and SU = self uncertainty; *p < 01. All effects displayed in this table are unstandardized.

Partner uncertainty as a mediator. The second model repeated the previous analyses, but used partner uncertainty as the mediating variable between the five sources of network uncertainty and relationship uncertainty (see Figure 6). This model demonstrated acceptable fit, $\chi^2(197) = 942.63$; $\chi^2/df = 4.79$; CFI = .92; and RMSEA = .084. For the *total effects* tests, only judging (β = .09) was positively and significantly related to relationship uncertainty. No other source of network uncertainty shared a significant association with relationship uncertainty (β < .06 in all cases).

For the *direct effect* tests, results displayed a significant and positive relationship for only judging (β = .06) on relationship uncertainty when controlling for partner uncertainty. No other source of network uncertainty was significantly related to relationship uncertainty when controlling for partner uncertainty.

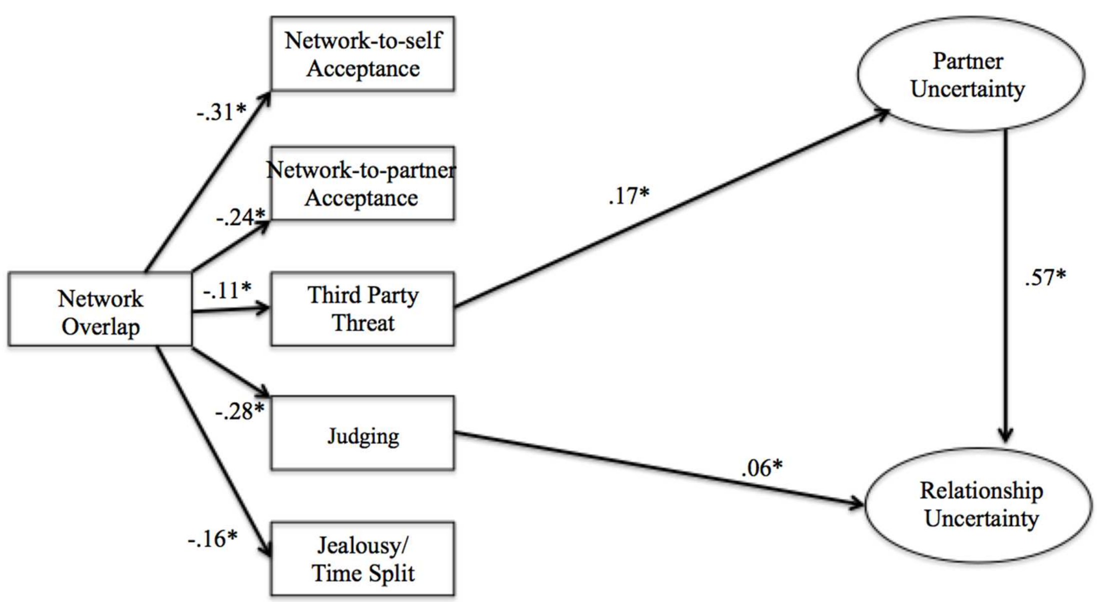

Figure 6. Associations between sources of network uncertainty and relationship uncertainty, mediated by partner uncertainty. All paths in this figure are standardized. For this model,□$\chi^2(197) = 942.63$; $\chi^2/df = 4.79$; CFI = .92; and RMSEA = .084. **p* < .01. Length of relationship is controlled for, but not shown in, this model.

Finally, the in*direct effect* tests revealed a significant indirect association between third party *threat* and relationship uncertainty ($\beta = .07$), mediated by partner uncertainty. No other source of network uncertainty was indirectly related to relationship uncertainty ($\beta < .03$ in all cases). Third party threat was positively related to partner uncertainty ($\beta = .17$), and the five measures of network uncertainty explained approximated 29% of the variation in partner uncertainty (i.e., $R^2 = .29$). Full tests of mediation can be viewed in Table 8.

Summary of multidimensional models. Overall, H7 was supported, as network overlap was a negative indicator of all five measures of network uncertainty. Additionally, the relationships between measures of network uncertainty and measures of relational uncertainty initially answer RQ1. To sum, there are four major findings presented in this section as they relate to the associations between sources of network and relational uncertainty First, the five sources of network uncertainty explained 41%, 29%, and 36% of variation in self, partner, and relationship uncertainty, respectively. Second, all five measures shared moderate direct relationships with self uncertainty. Moreover, all five sources of network uncertainty share small indirect associations with relationship uncertainty when using self uncertainty as a mediating variable. Third, only one measure of network uncertainty (third party threat) shared a significant direct relationship with partner uncertainty. Third party threat also indirectly related to relationship uncertainty when considering partner uncertainty as a mediating variable. Lastly, only judging shared a significant direct association with relationship uncertainty when considering partner uncertainty as a mediating variable.

Table 8

Effects of Sources of Network Uncertainty on Relationship Uncertainty, Mediated by Partner Uncertainty

			Total effect		Direct effect		Indirect effect		95% CI	
IV	DV	MV	Est.	SE	Est.	SE	Est.	SE	Upper	Lower
AS	RU	PU	.06	.026	.03	.029	.03	.018	.112	-.019
JU	RU	PU	.09*	.018	.06*	.031	.03	.017	.075	-.003
TpT	RU	PU	.05	.018	-.02	.036	.07*	.024	.133	.026
AP	RU	PU	.08	.022	.05	.043	.03	.021	.080	-.027
JT	RU	PU	.06	.023	.05	.029	.01	.019	.072	-.053

Note. AS = acceptance of self, JU = judging, TpT = third party threat, AP = acceptance of partner, JT = jealousy/time split, RU = relationship uncertainty, and PU = partner uncertainty; **p* < .01. All effects displayed in this table are unstandardized.

Mediation analyses with network uncertainty as unidimensional. The CFA of the network uncertainty measure revealed that the five measures of network uncertainty form a single, third-order, unidimensional latent variable. Because network uncertainty is a novel variable, it is unclear as to whether it should be measured as five distinct variables or one latent variable. As such, the mediating roles of self and partner uncertainty were tested again, this time treating network uncertainty as a singe latent construct rather than five distinctly measured variables. Moreover, the sum of squared correlations (i.e., R^2) was tested for network uncertainty as a latent variable.

For the second model assessing RQ1, network uncertainty was treated as a single, third-order, unidimensional latent variable. As with the multidimensional approach, models of self and partner uncertainty as mediating variables were tested separately.

Next, regression weights were assessed to determine significant relationships. For H7, network overlap shared a significant and negative relationship with network uncertainty (β = -.35). This provides full support for H7and demonstrates the importance of considering network overlap as a control variable when implementing measurements of network uncertainty.

Self uncertainty as a mediating variable. To better understand the relationship between network uncertainty and relational uncertainty as mediated by self uncertainty (RQ1), Preacher and Hayes' (2008) test of mediation was performed again, this time with network uncertainty as a single latent variable, rather than five measured variables. In this model paths were drawn from network uncertainty to self and relationship uncertainty. Second, a direct path was drawn from both self uncertainty to relationship uncertainty. The resulting model did not initially demonstrate adequate fit $\chi^2(205) = 1383.75$; χ^2/df = 6.75; CFI = .89; and RMSEA = .087. Consultation of modification indices revealed four necessary paths of covariation be drawn (between errors of individual measures within latent constructs) that ultimately resulted in good model fit $\chi^2(205) = 835.02$; χ^2/df = 4.07; CFI = .94; and RMSEA = .069.

For the *total effects* network uncertainty (β = .32) was positively and significantly associated with relationship uncertainty. These results provide an alternative answer to RQ1, in that network uncertainty shares a much stronger association with relationship uncertainty than do the five measured sources of network uncertainty when considered separately.

Next, the association between network uncertainty and relationship uncertainty while including self uncertainty was tested (i.e., the *direct effects* according to Preacher & Hayes, 2008). When controlling for self uncertainty, the direct effect between network uncertainty and relationship uncertainty was not significant ($\beta = .15$).

Finally, for the *indirect effects* (Preacher & Hayes, 2008) , the relationship between network uncertainty and relationship uncertainty was significant and positive when considering self uncertainty as a mediating variable ($\beta = .17$). As a latent variable, network uncertainty accounted for 60% of the variance in relationship uncertainty (i.e., $R^2 = .60$). Network uncertainty was positively and significant related to self uncertainty ($\beta = .77$) and explained 59% of variance (i.e., $R^2 = .59$). Lastly, self uncertainty ($\beta = .42$) was positively related to relationship uncertainty, supporting H8. Table 9 displays the total, direct, and indirect effects of the latent variable network uncertainty on relationship uncertainty (as mediated by self uncertainty).

Partner uncertainty as a mediating variable. Next a separate model was created when considering partner uncertainty as a mediating variable. In this model paths were drawn from the network uncertainty to partner and relationship uncertainty. Next, a direct path was drawn from both partner uncertainty to relationship uncertainty. The resulting model did not initially demonstrate adequate fit $\chi^2(205) = 1383.75$; $\chi^2/df = 6.75$; CFI = .89; and RMSEA = .087. Consultation of modification indices revealed six necessary paths of covariation be drawn (between errors of individual measures within latent constructs) that ultimately resulted in good model fit $\chi^2(205) = 835.02$; $\chi^2/df = 4.07$; CFI = .94; and RMSEA = .069.

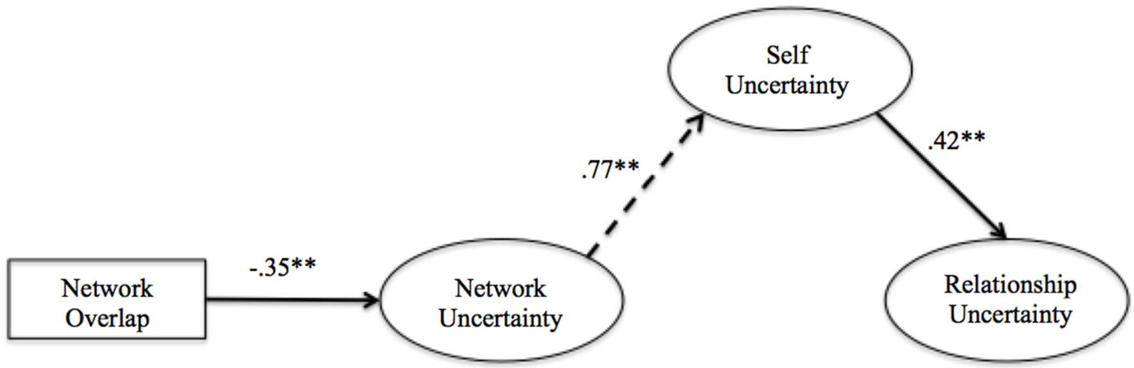

Figure 7. Path model for the effect of network uncertainty on relational uncertainty considering self uncertainty as a mediating variable. χ^2 (205) = 835.02; χ^2/df = 4.073, CFI = .94, RMSEA = .069. All estimates shown are standardized. For this model, *p < .01, ** p < .001. Dotted lines represent mediated paths. Network uncertainty is represented as a third order unidimensional variable. All variables in this figure are represented with ovals because this is a latent model (as opposed to a measured model). Length of relationship is controlled for, but not shown in, this model.

Table 9

Effects of Network uncertainty on Relationship Uncertainty, Mediated by Self Uncertainty

			Total effect		Direct effect		Indirect effect		95% CI	
IV	DV	MV	Est.	SE	Est.	SE	Est.	SE	Upper	Lower
NU	RU	SU	.37*	.044	.18	.080	.19*	.065	.349	.087

Note. NU = network uncertainty, RU = relationship uncertainty; SU = self uncertainty. *p < .01. Results demonstrated full mediation for self uncertainty when concerning the relationship between network uncertainty and relationship uncertainty. All effects displayed in this table are unstandardized.

First, the *total effect* of network uncertainty on relationship uncertainty was significant (β = .38). Again, the latent variable network uncertainty displayed a much stronger association with relationship uncertainty than did any one source of network uncertainty, further answering RQ1.

Next *direct effects* were assessed. When using partner uncertainty as a mediating variable, the relationship between network and relationship uncertainty was positive and significant (β = .21) at the critical alpha of .01.

Lastly, *indirect effects* were assessed. When considering partner uncertainty as a mediating variable, the indirect relationship between network and relationship uncertainty was positive and significant (β = .18). Similarly, network uncertainty was directly related to partner (β = .68) uncertainty. As a latent variable, network uncertainty explained 47% of the variation in partner uncertainty (i.e., R^2 = .47) Finally partner uncertainty (β = .58) was positively related to relationship uncertainty, supporting H8. Full results are displayed in Figure 8. See Table 10 for mediation results.

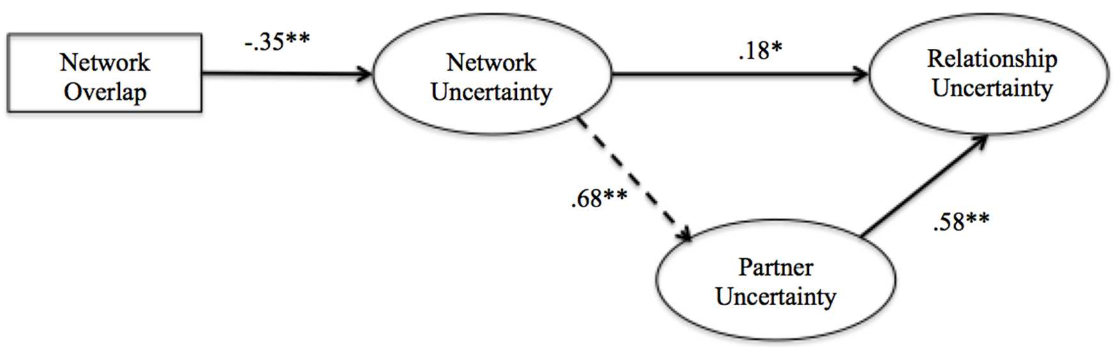

Figure 8. Path model for the effect of network uncertainty on relational uncertainty considering partner uncertainty as a mediating variable. χ^2 (205) = 835.02; χ^2/df = 4.073, CFI = .94, RMSEA = .069. All estimates shown are standardized. For this model, *p < .01, ** p < .001. Dotted lines represent mediated paths. Network uncertainty is represented as a third order unidimensional variable. All variables in this figure are represented with ovals because this is a latent model (as opposed to a measured model). Length of relationship is controlled for, but not shown in, this model.

Table 10

Effects of Network uncertainty on Relationship Uncertainty, Mediated by Partner Uncertainty

			Total effect		Direct effect		Indirect effect		95% CI	
IV	DV	MV	Est.	SE	Est.	SE	Est.	SE	Upper	Lower
NU	RU	PU	.43*	.034	.25*	.063	.18*	.033	.243	.072

Note. NU = network uncertainty, RU = relationship uncertainty; PU = partner uncertainty. **p* < .01. Results demonstrated partial mediation for partner uncertainty when concerning the relationship between network uncertainty and relationship uncertainty. All effects displayed in this table are unstandardized.

Summary of Unidimensional Models. In sum, there are three key takeaways from this analysis. First, as a latent variable, network uncertainty explained 59%, 47%, and 60% of the variance in self, partner, and relationship uncertainty, respectively. Given these results it is clear that network uncertainty is best used as a unidimensional measure rather than a multidimensional measure. Second, self uncertainty fully mediates the relationship between network uncertainty and relationship uncertainty. This is due to the significant *total* and *indirect* effects coupled with nonsignificant *direct* effects. For partner uncertainty, the *total, direct,* and *indirect* effects were all significant. Thus, partner uncertainty serves as a partial mediator for network and relationship uncertainty. These findings further specify the answer to RQ1.

Outcomes of relational uncertainty. The ninth hypothesis (H9) concerned associations between relational uncertainty (self, partner, and relationship) and perceptions of relational talk as threatening. Specifically, it was proposed that relationship uncertainty would directly and positively predict the perception that relational talk is threatening (H9a). Related, relationship uncertainty was said to partially mediate the relationship between self uncertainty and perceptions of relational talk as threatening (H9b), and fully mediate the relationship between partner uncertainty and perceptions of relational talk as threatening (H9c). These three predictions are directly posited by RTT. Lastly, the ability of network uncertainty to predict perceptions of relational talk as threatening – above and beyond self, partner, and relationship uncertainty – was tested (RQ2). Said differently, it is important to determine how, if at all, network uncertainty influences RTT variables beyond relational uncertainty.

The initial latent, hierarchical path analysis approached adequate fit, $\chi^2(321) =$ 1,868.22; $\chi^2/df = 5.82$; CFI = .91; and RMSEA = .079. Consultation of modification indices revealed four key necessary covariations between error factors within latent constructs. The resulting model demonstrated good-to-excellent fit, $\chi^2(321) = 1{,}138.26$; $\chi^2/df = 3.55$; CFI = .94; and RMSEA = .063. Standardized regression weights were assessed for all effects.

Preacher and Hayes's (2008) bootstrapping method of mediation was used to test H9. For the *total effects* (path C), self ($\beta = .44$), partner ($\beta = .54$), and relationship ($\beta =$ .22) uncertainty all shared a significant relationship with the perception of relational talk being threatening. Next, *direct effects* were observed (Path C'). Results showed that self ($\beta = .28$) but not partner ($\beta = .11$) uncertainty significantly and positively related to perceptions of relational talk as threatening when including relationship uncertainty as a moderating variable. Finally, *indirect effects* were assessed. There was a significant indirect relationship for self uncertainty on perceptions of relational talk as threatening (β = .16). Similarly, the indirect relationship between partner uncertainty and perceptions of relational talk as threatening (mediated by relationship uncertainty) was significant (β = .43). These associations demonstrate full support for H9 and are in line with the tenets of RTT. An illustration of the associations between relational uncertainty and perceptions of relational talk as threatening can be viewed in Figure 9. Unstandardized mediation effects can be seen in Table 11.

Next, network uncertainty was added to the model to observe how (if at all) it influenced perceptions of relational talk as threatening above and beyond self, partner, and relationship uncertainty (RQ2). The third-order variable was chosen for two reasons. First, treating network uncertainty as a single latent variable is more parsimonious. Second, and related, the results of RQ1 confirmed the explained variance and regression weights of network uncertainty are stronger as one variable, rather than five.

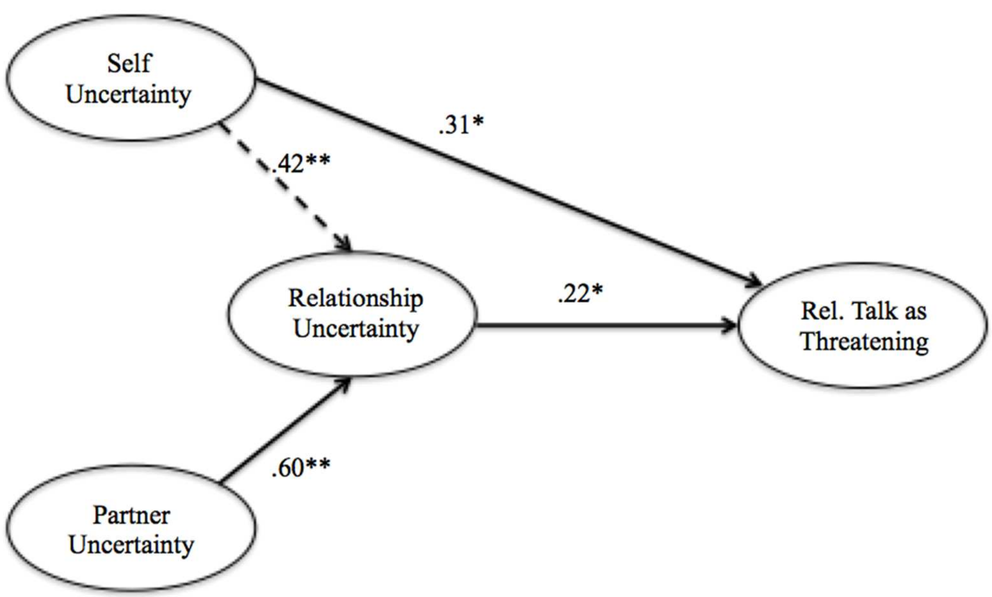

Figure 9. Associations between relational uncertainty and the perception of relational talk as threatening. $\chi^2(178) = 710.38$; $\chi^2/df = 3.99$; CFI = .96; and RMSEA = .068. All estimates shown are standardized. For this model, *$p < .01$, ** $p < .001$. All variables in this figure are represented with ovals because this is a latent model (as opposed to a measured model).

Table 11

Effects of Self, Partner, and Relationship Uncertainty on Perceptions of Relational Talk as Threatening

			Total effect		Direct effect		Indirect effect		95% CI	
IV	DV	MV	Est.	SE	Est.	SE	Est.	SE	Upper	Lower
SU	RT	RU	.45**	.054	.31*	.133	.14*	.062	.227	.014
PU	RT	RU	.60**	.039	.13	.123	.47**	.065	.625	.254

Note. SU = self uncertainty, PU = partner uncertainty; RU = relationship uncertainty; RT = perceptions of relational talk as threatening. *$p < .01$, **$p < .001$. Results demonstrated that relationship uncertainty partly mediates the association between self uncertainty and perceptions of relational talk as threatening, and fully mediates the association between partner uncertainty and perceptions of relational talk as threatening. All effects displayed in this table are unstandardized.

To test RQ2, a number of paths were drawn in a SEM. First, a path was drawn from network overlap to network uncertainty. Next paths were drawn from network uncertainty to self, partner, and relationship uncertainty as well as to the perception of relational talk as threatening. Additional paths were drawn from self uncertainty to relationship uncertainty as well as perceptions of relational talk as threatening. Paths were also drawn from partner uncertainty to both relationship uncertainty and the perception that relational talk is threatening. Finally, a path was drawn from relationship uncertainty to perceptions of relational talk as threatening. It should be noted that only one model was drawn to test RQ2. This is because it was important to observe how network uncertainty relates to biased cognitions while considering all three elements of relational uncertainty as simultaneous moderators (Preacher & Hayes, 2008).

The resulting model demonstrated good fit, $\chi^2(322) = 1{,}140.50$; $\chi^2/df = 3.54$; CFI = .94; and RMSEA = .063. Importantly, once network uncertainty was added to the model, the total effects of self ($\beta = .19$) and relationship uncertainty ($\beta = .09$) on perceptions of relational talk as threatening were no longer significant. On the other hand, network uncertainty displayed a strong positive association with perceptions of relational talk as threatening ($\beta = .29$). This finding represents the *total effects* column and can be seen in Figure 10.

Table 12 displays the results of the mediation tests. First, the mediating effects for self uncertainty were tested. When testing the *direct effects* of network uncertainty on relational talk as threatening with self uncertainty as a mediating variable, the relationship between network uncertainty and perceptions of relational talk as threatening was significant and positive, ($\beta = .15$). When observing the *indirect effects*, the relationship between network uncertainty and perceptions of relational talks as threatening was not significant ($\beta = .05$). Thus, self uncertainty does not serve as a mediating variable in this instance.

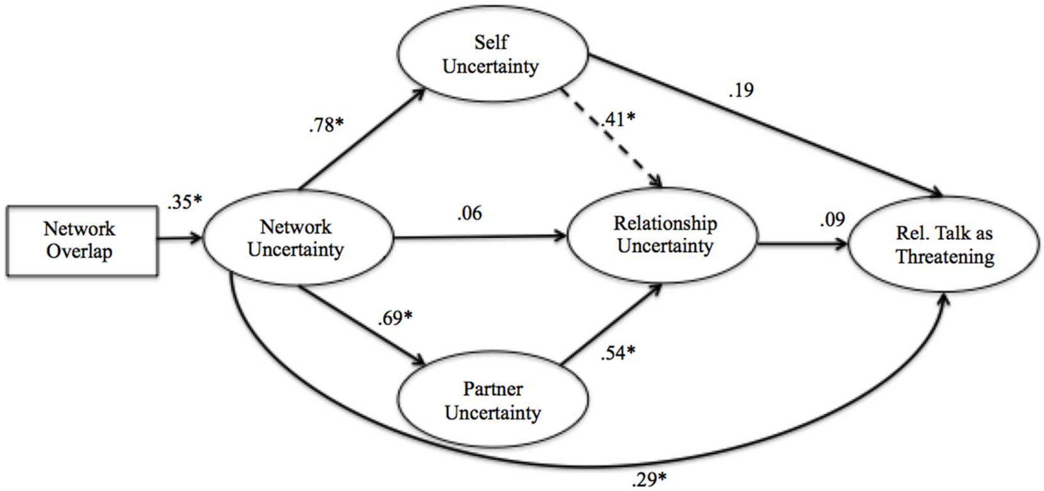

Figure 10. Associations between network uncertainty, relational uncertainty, and perceptions of relational talk as threatening. $\chi^2(322) = 1{,}140.50$; $\chi^2/df = 3.54$; CFI = .94; and RMSEA = .063. *$p < .001$. In this model, *network uncertainty* is represented as a third order unidimensional variable. Post-hoc regression results displayed similar results to the above model, such that self and relationship uncertainty were not significant indicators of perceptions of relational talk as threatening when controlling for network uncertainty.

Table 12

Tests of Mediation for the Latent Variable Relational Uncertainty on the Effects of Network Uncertainty on Perceptions of Relational Talk as Threatening

			Total effect		Direct effect		Indirect effect		95% CI	
IV	DV	MV	Est.	SE	Est.	SE	Est.	SE	Upper	Lower
NU	RT	SU	.35*	.061	.28*	.081	.07	.039	.134	.030
NU	RT	PU	.31*	.028	.30*	.123	.01	.055	.032	-.121
NU	RT	RU	.31*	.021	.27*	.112	.04	.043	.111	-.004

Note. NU = Network uncertainty, SU = self uncertainty, PU = partner uncertainty; RU = relationship uncertainty; RT = perceptions of relational talk as threatening. * $p < .01$. Results demonstrated that there is no mediating relationship for self, partner, or relationship uncertainty concerning the association between network uncertainty and perceptions of relational talk as threatening. All effects displayed in this table are unstandardized.

Next, partner uncertainty was assessed as a potential mediating variable between network uncertainty and perceptions of relational talk as threatening. For the *total effects* there was a significant and positive relationship between network uncertainty and perceptions of relational talk as threatening (β = .27). When testing the *direct effect* of network uncertainty on perceptions of relational talk as threatening (i.e., while controlling for partner uncertainty) results were significant (β = .26). When assessing *indirect effects* there was no significant indirect association between network uncertainty and perceptions of relational talk as threatening (β = .01). Thus, partner uncertainty does not serve as a mediating variable.

For relationship uncertainty as a mediating variable, the association between network uncertainty and perceptions of relational talks as threatening was significant and positive for *total effects* (β = .27). When testing *direct effects*, there was a significant relationship between network uncertainty and perceptions of relational talk as threatening while controlling for relationship uncertainty (β = .25). Finally, when testing *indirect effects*, there was no significant indirect relationship between network uncertainty and perceptions of relational talk as threatening (β = .02). In other words, relationship uncertainty does not serve as a mediator.

Thus, neither self, partner, nor relationship uncertainty mediates the relationship between network uncertainty and perceptions of relational talk as threatening. What is more, inclusion of the network uncertainty variable rendered the direct effects of self and partner uncertainty nonsignificant. These results answer RQ2 and are illustrated in Figure 10 and Table 12.

It is likely that the nonsignificant effects for self and relationship uncertainty on perceptions of relational talk as threatening are due to the high overlap in explained variance between self, partner, and relationship uncertainty. Because the three elements of relational uncertainty are so highly correlated, the effect of each individual variable is mitigated. It is reasonable to assume that network uncertainty is suppressing the effects of both self and relationship uncertainty on perceptions that relational talk is threatening. Bivariate correlations demonstrate strong relationships between the elements of relational uncertainty and the perception that relational talk is threatening. Moreover, Figure 9 displays significant paths for both self and relationship uncertainty with perceptions of relational talk as threatening.

Thus, an additional analysis was run in which self, partner, and relationship uncertainty comprised a latent variable (labeled *relational uncertainty*). This latent variable was placed parallel to network uncertainty in order to see how each latent construct influences the outcome variable. In this model, paths were drawn from network uncertainty to relational uncertainty and perceptions of relational talk as threatening. An additional path was drawn from relational uncertainty to perceptions of relational talk as threatening. The hierarchical model demonstrated good fit, $\chi^2(323) = 1{,}173.64$; $\chi^2/df = 3.63$; CFI = .94; and RMSEA = .064. Consultation of standardized regression weights showed that both network uncertainty ($\beta = .32$) and relational uncertainty ($\beta = .41$) positively contribute to the perception that relational talk is threatening. What is more, the R^2 for perceptions of relational talk as threatening increased from 22% of explained variance to 30% when adding network uncertainty into the model. Results of this test can be viewed in Figure 11.

Next, mediation was tested for using bootstrapping (Preacher & Hayes, 2008). The *total effect* of network uncertainty on perceptions of relational talk as threatening was significant and positive (β = .52). The *direct effects* indicated a significant positive relationship as well (β = .32). Finally, the *indirect effects* were also significant and positive (β = .20). Thus, the latent construct relational uncertainty partially mediated the relationship between network uncertainty and perceptions of relational talk as threatening. Results of mediation tests can be viewed in Table 13.

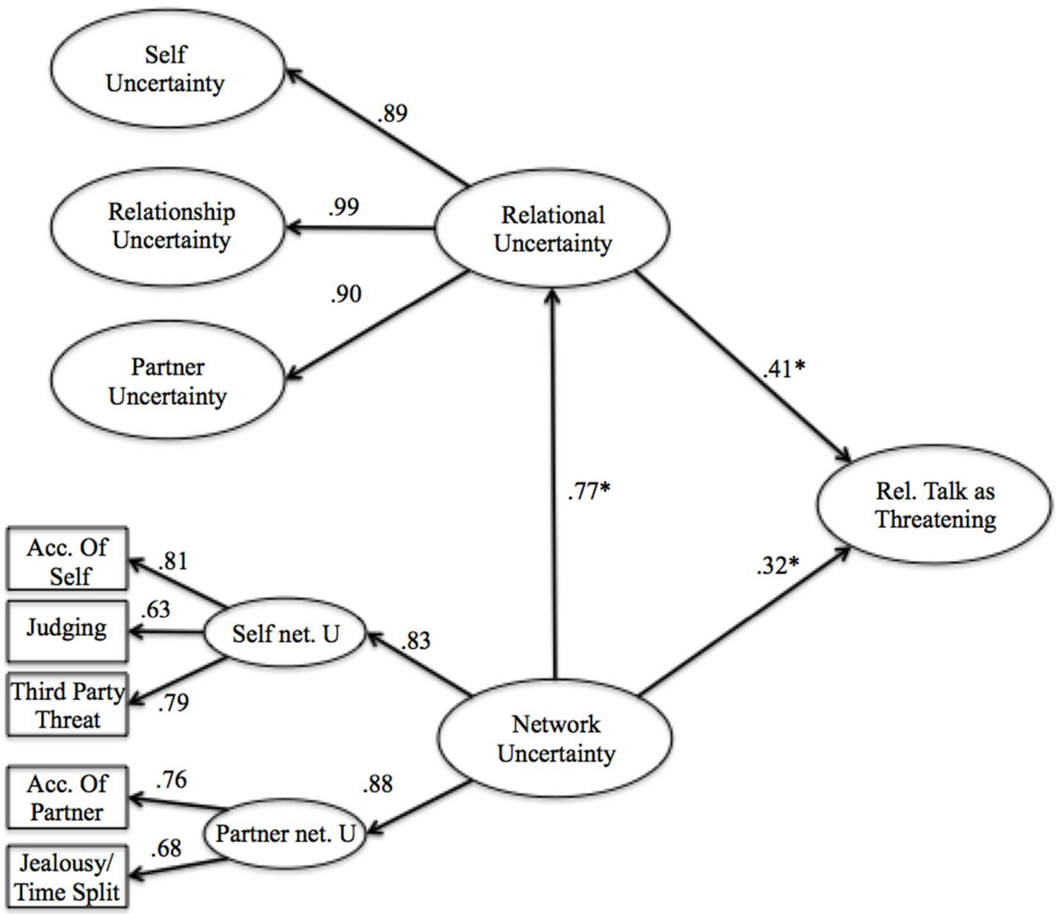

Figure 11. – Results of path analysis for relational uncertainty as a latent variable. $\chi^2(323) = 1{,}173.64$; $\chi^2/df = 3.63$; CFI = .94; and RMSEA = .064. $^*p < .001$.

Table 13

Tests of Mediation for the Latent Variable Relational Uncertainty *on the Effects of Network Uncertainty on Perceptions of Relational Talk as Threatening*

			Total effect		Direct effect		Indirect effect		95% CI	
IV	DV	MV	Est.	SE	Est.	SE	Est.	SE	Upper	Lower
NU	RT	RU	.86*	.061	.52*	.081	.34*	.039	.501	.137

Note. NU = Network uncertainty, RU = relational uncertainty; RT = perceptions of relational talk as threatening. * $p < .01$. Results demonstrated that there is partial mediation by the latent variable *relational uncertainty* on the effect of network uncertainty on perceptions of relational talk as threatening. All effects displayed in this table are unstandardized.

Network Interdependence: Tests of Divergent and Convergent Validity

The next series of hypotheses focuses associations between measures of network interference and facilitation and several RTT variables. Specifically it was predicted that measures of network interdependence would correlated with sources of partner interdependence (H10), negative emotion (H11), and perceptions of relational talk as threatening (H12). To test the convergent and divergent validity of network interdependence and facilitation a series of bivariate correlations were performed. Next, path analyses were performed to explore how network interdependence, partner interdependence, and negative emotions related to one another in a structural model. Correlations among all variables used in this study can be found in Appendix B.

First, it was predicted that both network interference (H10a) and network facilitation (H10b) would correlate positively with partner interference and facilitation. Results (see Table 14) indicated that network interference shares a positive relationship with partner interference, but not partner facilitation at the critical alpha of .01. This provides partial support for H10a. In addition, network facilitation correlated significantly and positively with both partner interference and partner facilitation. Thus H10b received full support.

Table 14

Bivariate Correlations Between Network Interdependence and Partner Interdependence

Measures	Partner Interference	Partner Facilitation
1. Network Interference	.55*	.15
2. Network Facilitation	.30*	.41*

Note. *$p < .001$

Hypothesis 11 posited that network interference would correlate positively with negative emotion (H11a), whereas network facilitation would correlate negatively with negative emotion (H11b). Bivariate correlations revealed that network interference shares a positive relationship with items indexing negative emotion. This provides full support for H11a. Contrary to H11b, network facilitation did not correlate significantly with measurements of negative emotion at the critical alpha of .01. These results provide partial support for H11. Full results can be viewed in Table 15.

Table 15

Bivariate Correlations Between Elements of Network Interdependence and Negative Emotion Concerning One's Relationship

Measures	Negative Emotion
3. Network Interference	.45*
4. Network Facilitation	-.17

Note. *$p < .001$

The 12th hypothesis focused on relationships between network interdependence and the perception that relational talk is threatening. Network interference was predicted to correlate positively with perceptions that relational talks is threatening (H12a). Conversely, network facilitation was predicted to correlate negatively with the perception that relationship talk is threatening (H12b).

Bivariate correlations indicated a positive correlation between network interference and perceptions of relational talk as threatening, supporting H12a. Results were inconsistent with H12b, as network facilitation did not share a significant relationship with perceptions of relational talk as threatening at the critical alpha of .01. Full results can be viewed in Table 16.

Table 16

Bivariate Correlations Between Elements of Network Interdependence and Perceptions of Relational Talk as Threatening

Measures	Rel. Talk as Threatening
5. Network Interference	.47*
6. Network Facilitation	-.18

Note. *$p < .001$

Network interdependence, partner interdependence, and negative emotions (concurrent validity). The final research question (RQ3) focused on how network interference and facilitation related to negative emotions while also considering the effects of partner interference and facilitation. This research question was approached in two ways. First, all four measured variables (network interference, network facilitation, partner interference and partner facilitation) were treated as distinct predictor variables, with negative emotion as the outcome variable. Second, tests of mediation were performed (Preacher & Hayes, 2008) such that partner interference and partner facilitation were positioned as potentially mediating the relationship between network interference and/or facilitation and negative emotions.

The first latent, hierarchical model (displayed in Figure 12) demonstrated excellent fit, $\chi^2(335) = 810.63$; $\chi^2/df = 2.28$; CFI = .97; and RMSEA = .045. Regression weights revealed a number of important results. First, partner interference (β = .38) and partner facilitation (β = -.33) were both significant predictors of negative emotions, although in opposite directions. Neither network interference (β = .15) or network facilitation (β = .07) shared a significant relationship with negative emotion. This demonstrates that there is not a direct relationship between measures of network interdependence and negative emotions. However, there may be an indirect relationship between these variables. Thus mediation was tested for.

For the second latent hierarchical model (testing mediation), Preacher and Hayes' (2008) bootstrapping method was applied again. This model demonstrated excellent fit, $\chi^2(358) = 840.09$; $\chi^2/df = 2.35$; CFI = .97; and RMSEA = .046. First, partner interference was considered as a mediating variable. For the *total effects* (i.e., path C), results revealed a positive significant total effect for network interference (β = .25) but no significant effect for network facilitation (β = -.03). Neither *direct effect* (i.e., path C') for network interference (β = .12) or network facilitation (β = -.02) was significant when controlling for partner interference. The *indirect effect* of network interference on negative emotion, using partner interference as a mediating variable (i.e., path AB), was significant and positive (β = .15). Because both the *total effects* were significant and the *direct effects* were nonsignificant, this demonstrates full mediation.

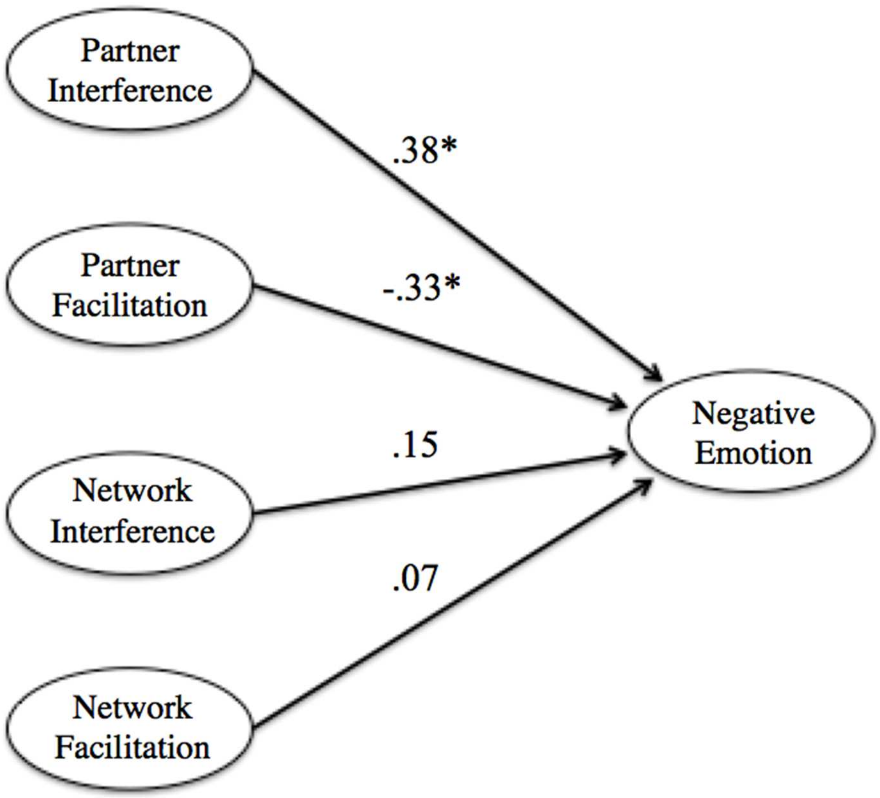

Figure 12. Path model regression lines for partner and network interdependence on experiences of negative emotions concerning one's relationships. $\chi^2(335) = 810.63$; $\chi^2/df = 2.28$; CFI = .97; and RMSEA = .045. All estimates shown are standardized. For this model, *p < .001. All variables in this figure are represented with ovals because this is a latent model (as opposed to a measured model). Length of relationship is controlled for, but not shown in, this model.

Network facilitation had no significant indirect effect (β = -.02) on negative emotions through partner interference. Thus, whereas partner interference fully mediates the relationship between network interference and negative emotion, no such indirect relationship exists between network facilitation and negative emotion. The results of partner interference as a mediating variable can be viewed in Figure 13, and full mediation results can be viewed in Table 17.

Next, partner facilitation was considered as the mediating variable. When testing *total effects*, neither network interference (β = .11) nor network facilitation was significant relationship with negative emotion (β = -.07). Initially, this suggests that partner facilitation does not serve as a mediating variable for network interference or facilitation and negative emotion. Analyses continued, however, to explore if the majority of explained variance by predictor variables was direct or indirect.

When testing *direct effects*, again, neither network interference (β = .11), nor network facilitation (β = .04) was significant related to negative emotion. Finally, when testing *indirect effects*, the relationship between network interference and negative emotion, using partner facilitation as a mediating variable, was not significant (β < .01). However, the indirect relationship between network facilitation (β = -.11) and negative emotion, with partner facilitation as a mediating variable, was significant and negative. This suggests, at first, that partner facilitation fully mediates the relationship between network facilitation and negative emotion. However, because the *direct* effects for network facilitation were positive and the *indirect effects* were negative, the significant result may be due to a suppression effect. Associations between all measures of interdependence (both network and partner) and negative emotion can be viewed in Figure 13. Tests of mediation can be seen in Table 17.

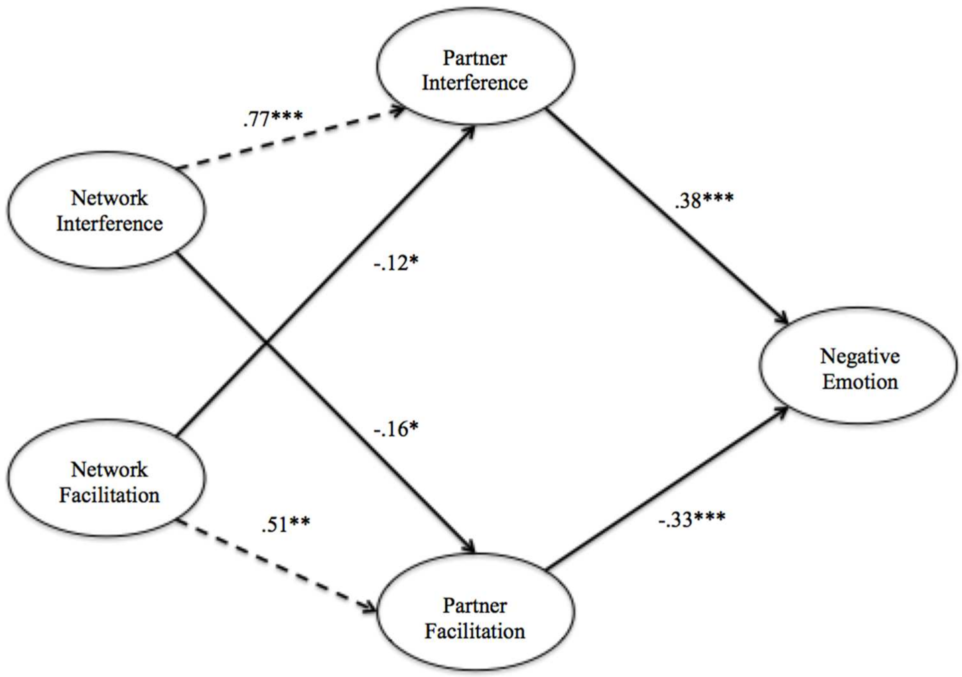

Figure 13. Tests of mediation between measures network interdependence, partner interdependence, and negative emotion. $\chi^2(358) = 840.09$; $\chi^2/df = 2.35$; CFI = .97; and RMSEA = .046. **p*< 01, ***p* < .001. Dotted lines represent mediated paths.

Table 17

Results of Partner Interference and Facilitation Mediating the Associations of Network Interference and Facilitation with Negative Emotion

			Total effect		Direct effect		Indirect effect		95% CI	
IV	DV	MV	Est.	SE	Est.	SE	Est.	SE	Upper	Lower
NI	NE	PI	.32*	.031	.11	.048	.21*	.051	.283	.139
NF	NE	PI	-.05	.045	-.02	.040	-.03	.028	.023	-.045
NI	NE	PF	.13	.033	.13	.023	.01	.032	.038	-.033
NF	NE	PF	-.08	.040	.05	.041	-.13*	.038	-.087	-.179

Note. NI = network interference; NF = network facilitation; PI = partner interference; PF = partner facilitation; NE = negative emotion concerning one's relationship. **p* < .01. Results demonstrated that partner interference partially mediates the relationship between network interference and negative emotions. Partner facilitation fully mediates the relationship between network facilitation and negative emotion. All effects displayed in this table are unstandardized.

Chapter 4

DISCUSSION

Extant theories of interpersonal communication have positioned relational success and failure as the result of (solely) dyadic interaction (e.g., Berger & Calabrese, 1975; Sunnafrank, 1986; Brashers, 2001; Solomon et al., 2016). Conversely, the social networks surrounding a couple have been shown to be important determinants of not only relational perceptions (Parks et al., 1983; Sprecher & Felmlee, 1992), but also relational outcomes (Parks & Adelman, 1983; Sprecher, 2011). Because the primary goal of theory is to predict, explain, and describe, theorists should strive to provide the most complete predictions, explanations, and descriptions within their tenets. The results of this dissertation demonstrate that the predictive and explanatory value of RTT benefit from the inclusion od social network-based variables. As such it stands to reason that both classical and contemporary interpersonal communication theories could benefit from network variables as well.

Indeed, extant scholarship has evidenced that breakup patterns (Agnew et al,. 2001), and relational processes in general (Parks et al., 1983; Sprecher, 2011) are a result of not only dyadic, but also network related episodes and perceptions. Given the need to include network processes and variables into previously dyadic interpersonal theories, the overarching goal of this dissertation was to integrate social-network based variables and processes into relational turbulence theory (Solomon et al., 2016). Broadly, that goal was accomplished. Specifically, this project placed and investigated the novel variables of network uncertainty (Stein & Mongeau, under review) and network interdependence (Stein, 2017) within the explanatory frame of RTT (Solomon et al.). Turbulence theory was a particularly good candidate to expand for two reasons. First, RTT is entirely dyadic and thus the predictive ability of the theory can be improved from inclusion of extra-dyadic variables. Second, research on previous iterations of the theory (i.e., the relational turbulence model) demonstrated that non-dyadic circumstances (e.g., transitions, Solomon et al., 2010) can lead to altered cognitive, emotional, and communicative episodes within dyads. For both network uncertainty and network interdependence, construct validity (in the form of convergent, divergent, and concurrent validity) was tested. Results demonstrated strong validity for each scale and point to a several important theoretical, practical, and interpersonal implications.

It appears as though network uncertainty is a unique measurement that can influence outcomes independent of relational uncertainty. This is evidenced by the tests of convergent, divergent, and concurrent validity. Similarly, measures of network interdependence appear to directly influence levels of partner interdependence and indirectly influence emotional outcomes. Theoretically, this illustrates an important determinant of dyadic interdependence, and highlights the ways in which a person's interchain sequence can be altered by both their partner and also by the individuals and groups surrounding his/her relationship. This discussion used the results of this dissertation to support the theoretical contributions of network uncertainty and network interdependence, respectively.

Implications for RTT

The most important question that this dissertation answered was the extent to which interpersonal communication theory can be improved by including social network variables. The use of social network uncertainty and interdependence as measured variables improved both the predictive and explanatory power of RTT. Said differently, inclusion of network variables paints a better picture of the mechanisms that lead people to question the nature of their relationship (i.e., explanation of how theoretical constructs relate to each other), as well as the reasons for why people may feel threatened by relational communication (i.e., predicting what factors increase perceptions of threat).

These results suggest that that other communication theories may benefit from the measurement of network perceptions including, but not limited to, network uncertainty and network interdependence. Taking partners' network perceptions into account may improve the explanatory or predictive power of other theories of uncertainty (e.g., Afifi & Weiner, 2004; Berger & Calabrese, 1975; Sunnafrank, 1986), or interdependence (Cook & Kenny, 2005; Petronio, 2002). This dissertation is evidence that exploring such endeavors is a worthwhile effort.

Specific to this manuscript's findings, it is clear that RTT benefits from inclusion of network uncertainty as a predictor variable the first panel of the theory's propositions (see Figure 1). Network uncertainty is very closely related to self and partner uncertainty conceptually. Both represent a degree of confidence that partners have in terms of relationship involvement. People make appraisals about their networks' acceptance and support of their relationship (Stein & Mongeau, under review). These appraisals, in turn, may alter the amount of involvement that they, or their partners, have in the relationship. It was thus predicted that levels of network uncertainty would directly relate to both self and partner uncertainty, while indirectly relating to relationship uncertainty.

Empirically, network uncertainty explains substantial variation in self, partner, and relationship uncertainty.. This improves the notion of relational uncertainty by suggesting that an entirely new set of processes (i.e., network appraisals) can aid in (or hinder) the turbulence process. Moreover the association between network uncertainty and biased cognitions above and beyond relational uncertainty speaks volumes to not only the usefulness of the measurement, but also its placement in the larger nomological network. The predictive power of RTT (specifically, the relationships between relational uncertainty and biased cognitions) increases greatly with the inclusion of network uncertainty (i.e., R^2 change = 8% when including network uncertainty). In short, network uncertainty improves RTT's explanatory value.

As shown in Figures 10 and 11, network uncertainty is an integral indicator of biased cognitions. This runs against not only some of the predictions made in this dissertation, but also the claims of RTT. Not only does network uncertainty explain additional variation in turbulence variables, it also points to an entirely new mechanism by which turbulence is generated. Thus, it may be useful to explore how the communicative enactment and valence of interactions with the network effects the broader perceptions of turbulence (see the second and third panel of Figure 1). Turbulence theory suggests that network disclosures are a result of relational turbulence (Solomon et al., 2016); however, network disclosures (and the communicative episodes that follow) may, over time, contribute to perceptions of relational turbulence.

For example, uncertainties concerning either network may alter future communication with network members (see the third panel of Figure 1), both in terms of whom a person chooses to communicate with, and about what topics. Moreover, uncertainties about network members may alter additional biased cognitions, such as relationship satisfaction (Knobloch & Theiss, 2011), appraisals of irritations (Solomon &

Knobloch, 2004), and perceptions of relational turmoil (Theiss & Knobloch, 2004). In other words, much in the way that relational uncertainty can lead to multiple biased cognitions, it is likely that network uncertainty explains additional (and meaningful) variance in these experiences.

Additional analyses sought to test potential indirect relationships between measures of network interdependence and negative emotions, using measurements of partner interdependence as mediating variables (in line with previous network-dyad research; Parks et al., 1983; Sprecher & Felmlee, 2000). In this dissertation, network interdependence is understood as the ways in which a person's social network interferes with or facilitates their everyday goal structure. There were strong direct associations between measurements of network interdependence and measurements of partner interdependence. Specifically, network interference and partner interference were strongly related, as were network facilitation and partner facilitation. The alternate relationships (i.e., network interference x partner facilitation and network facilitation x partner interference) were much weaker.

Results of RQ3 demonstrate that the extent to which a person's interchain sequence can overlap with not only his/her partner, but also his/her social network. In turn, a network's influence directly associates with a partner's influence, in terms of interfering and facilitating behaviors. In short, the strong relationships between network and partner interdependence them are in line with their conceptual definitions. This is meaningful in the context of RTT because it suggests that, in part, dyadic interdependence may be a result of network interdependence.

Indeed, as seen in both Figure 12 and Figure 13, there is no direct relationship between measures of network interdependence and negative emotion. However, there are indirect relationships shared by both network interference and network facilitation with negative emotion, mediated through partner interference and partner facilitation, respectively. The rationale for this dissertation is that relationships do not occur within a vacuum. That network and partner interdependence so closely relate to one another, and negative emotions, implies that RTT gains value from the inclusion of network interdependence. Admittedly, it appears although the value of network interdependence is not as great as the value of network uncertainty; however, network interdependence may be a more useful measure in other interpersonal theories, such as the investment model (Rusbult et al., 1994), or studies that make use of the actor-partner interdependence model (Cook & Kenny, 2005).

Scale Validation

One of the most important parts of scale development (and, by extension, theory expansion) is to ensure the convergent and divergent validity of a measure (Worthington & Whittaker, 2006). This dissertation featured two novel measurements (i.e., network uncertainty and network interdependence) in need of such tests. Network uncertainty, as a measured variable, contains five distinct subscales (acceptance of self, judging, third party threat, acceptance of partner, and jealousy/time split) whereas network interdependence contains two subscales (network interference and network facilitation). The seven subscales were correlated with several difference turbulence variables. Overall, results demonstrated empirical validity for all subscales, the implications of which are discussed below.

Network Uncertainty Convergent and Divergent Validity

All five sources of network uncertainty shared moderate-to-strong positive associations with self, partner and relationship uncertainty. Interestingly, judging consistently displayed the lowest correlations among all variables. This is especially curious given that judging displayed the highest mean for any source of uncertainty (both network and relational). It appears that although participants were most uncertain about being judged by their partners (compared to any other form of uncertainty), these uncertainties do not correlate with measurements of relational uncertainty strongly.

One explanation for this finding is that although relational partners place a great deal of weight on one another's relational judgments (e.g., Dillard, Solomon, & Samp, 1996), such consideration may not be paid to that of their partners' social networks. In other words, people simply may not believe that being judged by their partner's network is a particularly relationship threatening experience. That is not to say that people do not care *at all* about their partners' networks' judgments (as Driscoll et al., 1972, might suggest). Rather, in the context of network uncertainty, concerns about acceptance, third party threats, and jealousy may be more important than worries about judgment.

In short, subscales of network uncertainty are strongly related to self, partner, and relationship uncertainty, yet represent distinct constructs. Initially, this suggests that network uncertainty might be a unique role-player in the development of turbulence. Network uncertainty measures were, by far, most strongly related to relational uncertainty, compared to other turbulence variables. As such it is worth considering the relationship(s) between network uncertainty and relational uncertainty using more robust tests.

For the most part, measures of network uncertainty correlated with partner interdependence, negative emotions, and perceptions of relational talk as threatening. Once again, judging was either weakly or nonsignificantly related to these variables. This finding is likely due to (this form of) judging's inability to threaten the relationship directly. Network scholars have conceptualized judging behaviors as an element of network approval and/or support (e.g., Sprecher & Felmlee, 2001; Xu & Burleson, 2004). Participants may be particularly worried about being negatively judged by their partners' networks, but only allow these concerns to influence their relationship if they feel a lack of acceptance as well. Bivariate correlations are not a sufficient test of that hypothesis. A more detailed discussion of judging's role in RTT can be found in the discussion of path analyses.

For all but one source of network uncertainty (acceptance of self) correlations were stronger for valence of relational talk than for enactment of relational talk (i.e., number of times the conversation was brought up in the past week). Sunnafrank's (1986) predicted outcome value theory can provide insight to this trend, in that experiences of uncertainty do not necessarily lead to increased communication (such as increased enactment of relational talk), especially when the anticipated communication episode is negative (Ramirez, Sunnafrank, & Goei, 2010). According to POV, uncertainty does not necessarily lead to communication; rather, uncertainty allows people to make predictions about future interactions (Sunnafrank, 1986). Thus, the tenets of POV are a prime target for expansion via the inclusion of network uncertainty, as made clear by the results of bivariate correlations.

Together, the abundance of significant relationships between measures of network uncertainty and turbulence variables demonstrates enough evidence to inquire about theoretical expansion. Said differently, since network uncertainty relates so strongly and frequently to turbulence variables, it is worth seeing if RTT benefits from the inclusion of network uncertainty through more robust analyses (path analysis in this case). An important part of this process is testing each measure individually, but also considering that the five measures comprise a single unidimensional construct. Determining the structure of network uncertainty is important for not only theoretical expansion, but also for solidifying if the measure is exhaustive of all potential sources of network uncertainty.

Network Interdependence Convergent and Divergent Validity

In the past, network interdependence has been described using a series of attributes that arise from both dyadic interactions and network interactions within a group of individuals (see Surra, 1988); however, as a variable it has only been measured once (Stein, 2017). Confirmatory factor analysis revealed that the measured variables network interference and network facilitation represent variables that are empirically distinct from partner interference and partner facilitation. With this confirmation noted, several additional tests were employed to gauge the validity of the scale.

Network and partner interdependence subscales shared significant correlations, sans the relationship between network interference and partner facilitation. Although levels of a partner's interference are related to levels of partner facilitation, the network's interfering behaviors do not share that same relationship. This loosely reaffirms the work by Sinclair and colleagues (2014), which combats the claims of the Romeo and Juliet effect (Driscoll et al., 1972). Perhaps couples simply do not lean on each other for facilitating behaviors when they perceive their network is interfering with everyday goals. That said, it is likely that partner and network interdependence each contribute to the relational outcomes outlined in RTT.

Relevant to H11 (i.e., the relationship between network interdependence and negative emotion), results showed that negative emotions concerning one's relationship positively and significantly correlated with network interference but shared no relationship with network facilitation. These results are particularly important for the positions of RTT. Specifically, RTT claims that both interference and facilitation from partners predict heightened emotional reactions (although in opposite directions; Solomon et al., 2016). However, at the bivariate level, network interference meaningfully relates to negative emotion reactions, whereas network facilitation does not. Similar findings emerged for correlations with biased cognitions. These findings are in line with turbulence research, which has repeatedly demonstrated stronger effects for partner interference compared to partner facilitation (e.g., Knobloch & Donovan-Kicken, 2006; Knobloch & Theiss, 2011; Theiss & Solomon, 2006). Thus it appears that that interference from networks relates to relational outcomes (as suggested by Sprecher, 2011), but facilitation does not.

In sum, investigation of network interdependence convergent and divergent validity demonstrates that both subscales are viable. Specifically, these initial findings provide a warrant to test the concurrent value of network interdependence in the RTT framework. Since the larger goal of this dissertation was theory expansion, additional analyses were necessary to explore whether or not RTT benefits from the infusion of network variables. It is interesting to see network variables correlate with RTT variables; however, exploring the unique effects of network measurements as predictor variables is more important for the development of RTT and for the progression of interpersonal communication theory in general.

One important remaining question, prior to theory development, is the dimensionality of network uncertainty, which has been shown to fit confirmatory models as both a multidimensional and unidimensional variable (Stein et al., 2017). These tests were necessary to determine how (if at all) network uncertainty fits into RTT. Although network interdependence and facilitation comprise two separate dimensions, large intercorrelations among the five measures of network uncertainty, on the other hand, suggests that the measure might work better as one latent structure, rather than five measures. Answering this question was essential to the extension of RTT and also for the use of network uncertainty (network-based variables, more generally) in other communication theories. Confirmatory factor analysis and path models were used to test the competing models of network uncertainty and are discussed below.

The Dimensionality of Network Uncertainty

One of the most pertinent questions that emerged from this project was whether network uncertainty is best represented by five distinct measured variables (i.e., acceptance of self, judging, third party threat, acceptance of partner, and jealousy/time split; Stein & Mongeau, under review), or one global measure. This is a necessary step for theory revision. Because there is predictive value to be gained from including network uncertainty in RTT, it was necessary to observe which factor structure explains the most variance in RTT outcome variables.

Confirmatory factor analysis revealed that the 18 items measuring network uncertainty comprise five distinct factors; however, those five factors comprise two second-order unidimensional variables – one pertaining to uncertainties about a partner's network (self's network uncertainty) and one pertaining to uncertainties about one's own network (partner's network uncertainty). These two second-order factors, in turn, comprise a single third-order unidimensional variable (i.e., network uncertainty). This dimension reduction is important for two reasons. First, and most important to this project, the use of a third-order variable is often more parsimonious than first or even second-order variables (Rijmen et al., 2014). This makes for more straightforward additions to RTT, should the model fit.

Second, and most important for future research, the unidimensional factor structure suggests that experiences of network uncertainty are, like relational uncertainty, global in nature. Knobloch and Solomon (1999), in their initial measurement of relational uncertainty, noted the importance of capturing global perceptions of uncertainty, rather than uncertainties about specific behaviors. The current measure of network uncertainty, on the other hand, concerns specific behaviors that either network may engage in (e.g., worries about being judged, or purposefully interfered with, see Appendix A). Considering network uncertainty as a global variable would involve slightly modifying the existing measure, so as to capture broader uncertainties rather than uncertainties about specific behaviors. Such an effort would likely further reduce the number of items in a measure of network uncertainty, which generates greater parsimony and is easier to implement – both in RTT and in other interpersonal communication theories.

One potential disadvantage of the unidimensional structure of network uncertainty is that it may not capture the nuance that is accessible to first order variables. Thus, it was important to determine which measurement(s) of network uncertainty explained the most variation in RTT variables, and is the most practical for future and ongoing research. Thus, in this dissertation, both measurements of network uncertainty were considered during substantive analyses: first as five distinct variables, and then as a third order variable.

Network Uncertainty and Relational Uncertainty

It was first pertinent to explore how network uncertainty is related to self, partner, and relationship uncertainty. Specifically, this dissertation sought to explore if network uncertainty is a) a fourth element of relational uncertainty, b) a unique variable that influences variables independent of self, partner, and relationship uncertainty, or c) a measure that relates to other variables *through* self, partner, and/or relationship uncertainty. The first step in this process was to explore the associations between network and relational uncertainty. Ultimately, answering this query will help to determine how RTT can be improved by incorporating network uncertainty.

Network uncertainty as multidimensional. Both the direct and indirect effects of network uncertainty measurements on relationship uncertainty were tested, considering both self and partner uncertainty as mediators. These relationships were assessed in two ways: the direct relationship between (measures of) network uncertainty and relationship uncertainty, and the indirect relationship between (measures of) network uncertainty and relationship uncertainty (as mediated by self and/or partner uncertainty).

First, the five subscales of network uncertainty are, for the most part, not directly related to relationship uncertainty. In this way network uncertainty appears not to be a fourth element of relational uncertainty. Theorists (e.g., Solomon et al., 2010) have argued that relationship uncertainty must stem from self and/or partner uncertainty. The lack of a direct association between sources of network uncertainty and relationship uncertainty suggest that either a) network uncertainty is a precursor to self and partner uncertainty, or b) it is a completely distinct variable. As such, indirect relationships were observed next.

All five measures of network uncertainty were significantly related to self, but not partner, uncertainty (see Figure 5 and Figure 6, respectively). Only third party threat was significantly related to partner uncertainty. In both cases, regression weights were small-to-moderate, but it is clear that the elements of network uncertainty are more closely related to self rather than partner uncertainty.

That measures of network uncertainty are more consistently related to self rather than partner uncertainty is an important discovery. It appears that concerns about acceptance (from either network), judging, third party threats, and jealousy/time split issues are enough to make someone question their own involvement in a relationship, but perhaps not question their partners' involvement. This is important because self uncertainty is directly related to relational outcomes (i.e., biased cognitions) above and beyond relationship uncertainty (see Solomon & Theiss, 2006; Theiss & Nagy, 2013; Solomon et al., 2016). From a theoretical standpoint, this suggests that network uncertainty might lead to self uncertainty at a later time. If this is the case, network uncertainty may be an additional generative mechanism in RTT, one that both predicts and works in tandem with self uncertainty.

When measuring network uncertainty as five distinct sources, important trends emerged. First, relationships between all five sources of network uncertainty and both self (and the one significant relationship with partner) uncertainty were small-to-moderate, suggesting that are related, but empirically distinct, experiences. Second, individual relationships between measures of network and relationship uncertainty were typically small. The summed square of correlations (i.e., R^2) for self, partner, and relationship uncertainty, however were strong. In other words the five measures of network uncertainty explained a strong amount of variance in self, partner, and relationship uncertainty, despite modest individual regression weights.

Ultimately, the goal of this dissertation was to expand the value of RTT. That measures of network uncertainty accomplished this goal is encouraging. However, CFA demonstrated that network uncertainty may explain more variation, more parsimoniously as a single unidimensional structure rather than five measured variables. In order to properly test whether or not network uncertainty represents one variable or five, identical path analyses needed to be performed with network uncertainty as a third-order unidimensional variable.

Network uncertainty as unidimensional. Confirmatory factor analysis revealed that the five sources of network uncertainty comprise a single, third order latent variable (labeled network uncertainty). One important question is the extent to which, if at all, tests of direct and indirect effects between network and relational uncertainty differ when considering network uncertainty as one variable, rather than five.

Tests of RQ1 imported the value of network uncertainty as unidimensional measure, rather than five separate variables. Effects of network uncertainty on self, partner and relationship uncertainty were more pronounced than for the five sources considered individually. This was also true for the sum of squared correlations (R^2) for self, partner, and relationship uncertainty. In other words, not only is network uncertainty more strongly related to self, partner, and relationship uncertainty as a unidimensional measure, it also explains more variance in each of the three outcome variables. Therefore, network uncertainty should be measured as one factor, not five.

Self uncertainty fully mediated the effects of network uncertainty on relationship uncertainty whereas partner uncertainty partially mediated this relationship. Broadly, this reiterates the initial Stein and colleagues' (2017) finding that network uncertainty is both directly and indirectly related to relationship uncertainty. From a theoretical standpoint, these results demonstrate two things. First, these findings confirm that people's uncertainties about non-dyadic entities (originally suggested by Knobloch & Donovan-Kicken, 2006) do influence relationship evaluations (i.e., relational uncertainty). Whereas RTT suggests that communication with the social network is a result of turbulence (Solomon et al., 2016), the results of this dissertation suggest that the social network(s) surrounding a couple may also contribute to dyadic perceptions such as relational uncertainty, rather than exclusively stem from them. If this is the case, the feedback loop featured in RTT may also be in need of revision. Longitudinal data collection will be necessary to confirm this hypothesis.

Second, and related, these results call to attention the exogenous status of self and partner uncertainty in RTT. Turbulence scholars do not consider the antecedents of relational uncertainty and claim that the process of relational turbulence begins with the self or the partner. Contrary to this assumption, the present results imply that there may in fact be cognitions and behaviors that systematically precede and produce self or partner uncertainty. For example, if a person's confidence in their relationship can be shaken by the thought that someone is tempting his/her partner to cheat (i.e., third party threat), or that his/her partner is unduly jealousy of a perfectly innocent relationship (jealousy/time split), it may lead him/her to question his/her own (or his/her partner's) involvement in the relationship. Moreover, concerns about network approval have been shown to influence relational stability (Sprecher, 2011). The culmination of these doubts is certainly associated with experiences of self, partner, and relationship uncertainty, but causal claims cannot yet be made.

With a more complete understanding of the empirical nature of network uncertainty, theoretical tests were necessary to determine how inserting network uncertainty (as one factor) fits into RTT. This final step is important for the extension of RTT, and also for justifying future interpersonal theory expansions. If network uncertainty fits conceptually and empirically within the framework of RTT, it will provide evidence for testing network-based variables (including network uncertainty) within the tenets of other communication theories.

Network Uncertainty and Relational Uncertainty Outcomes in RTT

The most important development of this dissertation was the incorporation of network uncertainty into the first and second panel of RTT (RQ2; see Figure 10). Without network uncertainty, self and relationship uncertainty strongly predicted perceptions of relational talk as threatening. When network uncertainty was included in the model, however, the effects of self and relationship uncertainty became nonsignificant. This may be because self, partner, and relationship uncertainty are so strongly related that including another variable (i.e., network uncertainty) that strongly predicts all three components eliminates the moderators' influences. Therefore, to eliminate the strong intercorrelations of self, partner, and relationship uncertainty, a separate path analysis was performed that combined relational uncertainty components into a single latent variable (labeled relational uncertainty). As displayed in Figure 11, both relational uncertainty network uncertainty variables were significant (and substantial) predictors of perceptions of relational talk as threatening. In other words, once the overlapping variance of self, partner, and relationship uncertainty are controlled for, relational uncertainty does significantly correlate with perceptions of relational talk as threatening. Moreover, relational uncertainty partially mediated the influence of network uncertainty on perceptions that relational talk is threatening. In summary, network uncertainty both directly and indirectly (through relational uncertainty) influences perceptions that relational talk is threatening.

Differences between Figures 10 and 11 foreground an important issue, specifically, the unique role of network uncertainty in RTT. Analyses (particularly those focusing on RQ2) demonstrate that network uncertainty acts independently (in part at least) of self, partner, and relationship uncertainty to predict biased cognitions. This is consistent with previous research (e.g., Felmlee, 2001; Parks et al., 1983) that has demonstrated network perceptions (e.g., liking, approval, and support) can associate with relational perceptions and outcomes when controlling for dyadic perceptions. Even though network uncertainty is strongly associated with all three elements of relational uncertainty (see Figures 7 and 8), it produces unique variance in biased cognitions (e.g., the perception that relational talks is threatening). Thus, future research should position network uncertainty as independent from (but also as a predictor of) relational uncertainty when performing analyses.

Despite the fact that network uncertainty strongly influences biased cognitions, it is worth noting that RTT considers self, partner, and relationship uncertainty as distinct factors. Thus, performing analyses with the three elements combined into a single latent variable violates the theory's suppositions (see Solomon et al., 2016). As such, these results should be interpreted with caution. Moreover, action should be taken to explore associations between network and relational uncertainty without comprising a latent variable that violates theoretical predictions. Once such way involves altering network uncertainty measures to reflect more global (rather than behavioral) perceptions. Another option would be to explore alternate measures of relational uncertainty (such as those recently used by Solomon and Brisini, in press).

To summarize, although network and relational uncertainty are closely related, it appears as though the measurement of network uncertainty is empirically distinct from self, partner, and relationship uncertainty. Confirmatory factor analysis and path analysis but support this declaration. Moreover, relational and network uncertainty influence outcomes in unique ways. This finding reaffirms the usefulness of network uncertainty as a measure and demonstrates one way in which the measure improves RTT.

As mentioned previously, longitudinal data will be necessary to determine if network uncertainty *leads* to a) relational uncertainty and b) relational cognitions above and beyond relational uncertainty. Answering this question would solidify the extent to which network uncertainty improves the predictive and explanatory value of RTT.

Network Interdependence, Partner Interdependence, and Negative Emotions

The final research question of this dissertation (RQ3) focused on how, if at all, measures of network interdependence relate to negative emotions when controlling for measures of partner interdependence. Results of RQ2 demonstrated that network uncertainty explains variation in biased cognitions beyond that of relational uncertainty. Similarly, tests of RQ3 detailed how network interdependence improves the value of the bottom portion of Figure 1, panel one. Said differently, this final test explored how network interdependence improves the second generative mechanism in RTT.

Bivariate correlations indicated that network interference is more strongly related to negative emotions than is network facilitation. Path analyses, on the other hand, showed that neither network interference nor network facilitation shared significant relationships with negative emotions. Partner interference and facilitation, on the other hand, were significantly related to negative emotions. These results are a clear indication that dyadic interdependence is more likely to result in negative emotional evaluations of one's relationship than network interdependence.

The most reasonable explanation for these nonsignificant findings focuses on the locus of the emotions. Specifically, in this study, the measure of negative emotions focused on participants' sadness, anger, and fear when considering their romantic relationships (as predicted by RTT), as opposed to their network relationships. Although interfering (Sprecher, 2011) and facilitating (Xu & Burleson, 2004) behaviors from network members can alter dyadic perceptions, these variables appear not to influence anger, sadness or fear directed toward one's relationship or partner. On the other hand, a partner's interference (Knobloch et al., 2007) and/or facilitation (Solomon & Knobloch, 2004) can certainly spark emotional reactions about that relationship. Accordingly, perceptions of network interdependence may be related to negative emotions concerning specific network members, or the entire social network.

Indeed, much of the rationale for this dissertation explains that people are in multiple simultaneous relationships. As such, some processes (partner interdependence) might create dyadic effects while others (network interdependence) will produce network effects. What is more, it may be that dyadic processes result in network effects, and vice-versa. In the case of RTT, network interdependence is clearly important, but perhaps not as much of a relational determinant as dyadic interdependence.

Additional analyses sought to test potential indirect relationships between measures of network interdependence and negative emotions, using measurements of partner interdependence as mediating variables (in line with previous network-dyad research; Parks et al., 1983; Sprecher & Felmlee, 2000). There were strong direct associations between measurements of network interdependence and measurements of partner interdependence. Specifically, network interference and partner interference were strongly related, as were network facilitation and partner facilitation. The alternate relationships (i.e., network interference x partner facilitation and network facilitation x partner interference) were much weaker.

Results of RQ3 (see figures 12 and 13)demonstrate that the extent to which a person's interchain sequence can overlap with not only his/her partner, but also his/her social network. In turn, a network's influence directly associates with a partner's influence, in terms of interfering and facilitating behaviors. In short, the strong relationships between network and partner interdependence are in line with their conceptual definitions. This is meaningful in the context of RTT because it suggests that, in part, dyadic interdependence may be a result of network interdependence. This should be especially true in fledging relationships, in which ties with the network are likely stronger than ties with the partner (Sprecher & Felmlee, 1992). On the other hand, close committed relationships (such as those in this study) are likely more closely tied to their partners. As such, the effects of network interdependence are likely less meaningful.

Indeed, as seen in both Figure 12 and Figure 13, there is no direct relationship between measures of network interdependence and negative emotion. However, there are indirect relationships shared by both network interference (mediated through partner interference) and network facilitation (mediated by partner facilitation) on negative emotion. The rationale for this dissertation is that relationships do not occur within a vacuum. That network and partner interdependence so closely relate to one another, and negative emotions, implies that RTT gains value from the inclusion of network interdependence.

Moving Beyond RTT

Broadly, results of this dissertation suggest that uncertainties about networks could be useful in other impersonal theories as well. Too often interactions with the social network are considered an outcome of relational interaction. For example, communication privacy management theory (Petronio, 2002) explains that network members often take ownership of the private information that is shared with them. The theory discusses determinants of information sharing, but does not take into account why certain people (e.g., confidants) are chosen to co-own information. Network uncertainty may, in part, determine which network member(s) people choose to discuss their relationships with.

Moreover, decisions about whether or not to seek information from network members might be explained by the theory of motivated information management (TMIM; Afifi & Weiner, 2004). Per the TMIM, considerations of predicted outcomes and efficacy in information seeking may be, in part, influenced by the degree to which a person is unsure of his/her network's perception of his/her relationship. Moreover, communication accommodation theory (Giles, 2008) involves perceptions of social network involvement in the altering of one's language use. The uncertainties that one has about his/her network in regards to (for example) intercultural relationships (Triandis, Bontempo, Villareal, Asai, & Lucca, 1988) may dramatically alter the way that he/she communicates with both his/her network and his/her partner. People tend to alter their communication in the name of appeasing or (sometimes) defying other people (Giles). It is reasonable to suggest that uncertainties regarding a person's networks (such as reference groups) partially guide such behaviors.

The usefulness of network interdependence may expand beyond RTT as well. Given that over one third of partners believe that meddling from network members can shape relational persistence (Felmlee, 2001), measurements of network interference and facilitation should be considered as predictor variables within interpersonal communication theories as well. For example, POV explains that uncertainty reduction is attempted only when people predict positive outcomes (Sunnafrank, 1986). Predictions that network members will facilitate relational development and everyday goals may lead people to seek their networks' advice about their close relationships. On the other hand, predictions of network interference may result in active information avoidance.

One gesture toward this trend is evident in existing social network research. People who predict negativity from their networks at one point in time are less likely to remain in their romantic relationship at a later point in time (Sprecher & Felmlee, 2000). On the other hand, those who expect support from their networks maintain relational persistence (Xu & Burleson, 2004). It is likely that a lack of communication with networks (and subsequent relational failure) partially stems from perceptions of network interference and facilitation. The results of this dissertation are a starting point toward advancing a number of interpersonal communication theories in addition to RTT. Admittedly, it appears although the value of network interdependence is not as great as the value of network uncertainty; however, network interdependence may be a more useful measure in other interpersonal theories, such as the investment model (Rusbult et al., 1994), or for studies/theories that make use of the actor-partner interdependence model (Cook & Kenny, 2005).

In short, network uncertainty and network interdependence measures are certainly useful across a bevy of interpersonal theories. More broadly, the results of this dissertation call for a remodeling of existing communication theory. As articulated in the early chapters of this manuscript, most interpersonal theories insist that relationships develop within a vacuum, and that only the two individuals in a relationship can influence its outcomes. Interpersonal communication research must consider in influential role of the network in the formation (Sprecher, 2011), maintenance (Parks et al., 1983; Sprecher & Felmlee, 2000), and termination (Agnew et al., 2001; Parks &

Adelman, 1983; Xu & Burleson, 2004) of close relationships. This may entail novel conceptualizations and measures of network involvement, as well as the modification of existing measures to account for network perceptions and behaviors. This dissertation is a necessary and initial step toward that ultimate outcome.

Limitations and Future Directions

Although the results of this study provide useful information to both interpersonal communication and social network studies, a number of limitations should be recognized. First, no causal claims can be inferred from these results, as data collection was cross-sectional. Longitudinal data will be necessary to determine the order of causal relationships between variables. For example, it may be that although network uncertainty shares a positive association with both relational uncertainty and biased cognitions, network uncertainty may not lead to either of these experiences at a later point in time. Similarly, if network interdependence at time 1 does not predict partner interdependence at time 2, it may be useful as a control variable, but not as much else. Future research should explore these potential relationships so as to determine the causal influence of social networks on relational turbulence processes.

Second, although the measurement of network uncertainty has already undergone a series of dimension reductions, further consolidation is necessary. The results of CFA demonstrated that network uncertainty, represented as a third-order unidimensional variable, is comprised by both self's network and partner's network uncertainties. Moreover, measurements of relational uncertainty (Knobloch & Solomon, 1999; Solomon & Brisini, in press) are more global in nature, whereas measurements of network uncertainty often pertain to specific behaviors.

Thus, a refined measurement of network uncertainty should be crafted that a) shortens the current 18 item scale and b) pertains to more global perceptions rather specific sources of uncertainty. Such a measure would reflect general perceptions of network-self and network-partner relations. The themes of acceptance, judging, jealousy, threat and time split would be maintained; however, specific behaviors would not be discussed in such a matter. Moreover, minor shifts in the wording of uncertainty measures have been shown to elicit higher means of uncertainty, likely due to increased comprehension by participants (Solomon & Brisini, in press). Future measures of network uncertainty should explore similar modifications.

Finally, the present results might be interpreted to suggest that network interdependence scales have limited utility. The negative results may be a function of the choice to measure negative emotions *about participants' romantic* relationship. Had the negative emotions measured been more global (e.g., "overall, I feel…*sad*, *mad*, *fearful*), or even specifically directed toward network members, the direct effect of network interdependence might have been more prominent. In other words, future research should explore how network interdependence affects perceptions of network relationships, rather than romantic relationships.

As such, future research should not only explore the usefulness of network perceptions in other interpersonal theories, but also aim to craft a theory of network-dyad interaction. Such a theory would likely involve the use of dyadic, triadic, or even quadratic data (i.e., network analysis) and would ultimately paint a more complete (though more complex) picture of the ways in which social networks interact with romantic partnerships.

Concluding Thoughts

The primary goal of this dissertation was to incorporate social network variables into RTT to explore how, if at all, network perceptions are associated with dyadic and relational cognitions/emotions. This was a necessary step in arguing for a more network-focused perspective on communication theory, in general. This goal was certainly met. The results of this investigation provide the springboard for theory refinement (such as RTT) and development. Given the present results, future research should be able to determine just how important network perceptions are in the context of interpersonal relationships, and how social networks interact with romantic dyads, writ large.

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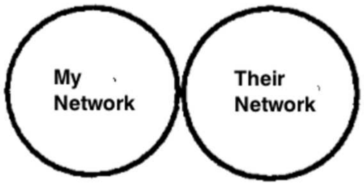
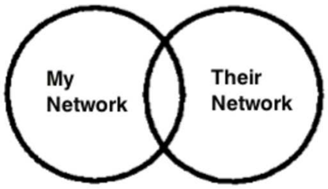
APPENDIX A

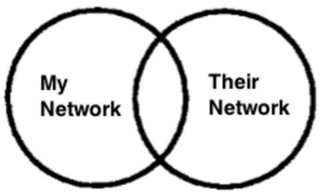
LIST OF SCALES TO BE USED IN THE CURRENT PROJECT

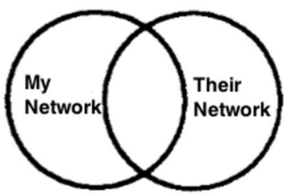
I. Network Overlap

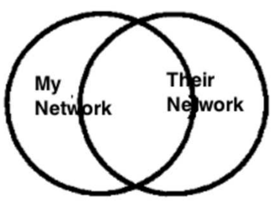
To what degree do you believe your social network overlaps with your partner's?

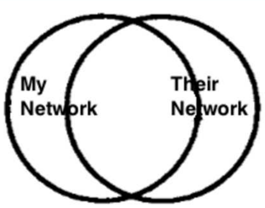


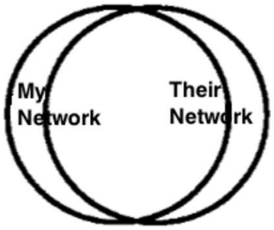




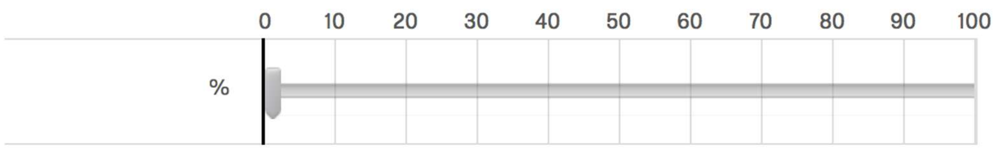








Based on your answer above, what percentage do you believe your social network overlaps with your partner's? 0% would mean that you do not know anyone from your partner's network and they do not know anyone from yours. 50% would mean that you and your partner each know a fair amount of your respective networks. 100% would mean that you and your partner are both familiar with everyone who is in both of your lives.



II. Relational Uncertainty

The following questions will be used to measure relational uncertainty

In the following section, we have listed a number of statements addressing different facets of involvement in dating relationships. We would like you to rate how CERTAIN you are about the degree of involvement that you have in your romantic relationship.

Please note: We are not asking you to rate how much involvement there is in your dating relationship, but rather how certain you are about whatever degree of involvement you perceive. It might help you first consider how much each form of involvement is present in your dating relationship, and then evaluate how <u>certain</u> you are about that perception.

For these judgments you should use the following scale:

1	2	3	4	5	6	7
COMPLETELY OR ALMOST COMPLETELY UNCERTAIN	MOSTLY UNCERTAIN	SOMEWHAT UNCERTAIN	NEUTRAL	SOMEWHAT CERTAIN	MOSTLY CERTAIN	COMPLETELY OR ALMOST COMPLETELY CERTAIN

We would like to know how certain you are about YOUR OWN INVOLVEMENT in your relationship.

HOW CERTAIN ARE YOU ABOUT…

1. Whether or not you want the relationship to work out in the long run?
2. Whether or not you want the relationship to last?
3. How much you like your partner?
4. How important the relationship is to you?
5. How much you are romantically interested in your partner?
6. **Whether or not you are ready to commit to your partner?**

Next, we would like to know how certain you are about YOUR PARTNER'S INVOLVEMENT in your relationship.

1	2	3	4	5	6	7
COMPLETELY OR ALMOST COMPLETELY UNCERTAIN	MOSTLY UNCERTAIN	SOMEWHAT UNCERTAIN	NEUTRAL	SOMEWHAT CERTAIN	MOSTLY CERTAIN	COMPLETELY OR ALMOST COMPLETELY CERTAIN

HOW CERTAIN ARE YOU ABOUT…

1. Whether or not your partner is ready to commit to you?
2. How committed your partner is to the relationship?
3. Whether or not your partner wants to be with you in the long run?
4. How important the relationship is to your partner?
5. Whether or not your partner wants the relationship to work out in the long run?
6. **How much your partner is attracted to you?**

Next, we would like to know how certain you are about facets of YOUR RELATIONSHIP, in general.

1	2	3	4	5	6	7
COMPLETELY OR ALMOST COMPLETELY UNCERTAIN	MOSTLY UNCERTAIN	SOMEWHAT UNCERTAIN	NEUTRAL	SOMEWHAT CERTAIN	MOSTLY CERTAIN	COMPLETELY OR ALMOST COMPLETELY CERTAIN

HOW CERTAIN ARE YOU ABOUT…

1. Whether or not the relationship will work out in the long run?
2. Whether or not you and your partner feel the same way about each other?
3. Whether or not you and your partner will stay together?
4. Whether or not you relationship is a romantic one?
5. The boundaries for appropriate and/or inappropriate behavior in the relationship?
6. Whether or not your partner likes you as much as you like him/her?
7. **How you can or cannot behave around your partner?**

*Note. Bolded items were removed from analysis during EFA.

III. Network Uncertainty

As you read the statements below, please consider ONLY interacting with **your partner's social network** (close friends, family members, peers/coworkers, etc.). As you think about your past, current, and future interactions with your partner's social network, indicate your current level of CERTAINTY about the following statements (*1 = COMPLETELY OR ALMOST COMPLETELY UNCERTAIN; 7 = COMPLETELY OR ALMOST COMPLETELY UNCERTAIN*).

1	2	3	4	5	6	7
COMPLETELY OR ALMOST COMPLETELY UNCERTAIN	MOSTLY UNCERTAIN	SOMEWHAT UNCERTAIN	NEUTRAL	SOMEWHAT CERTAIN	MOSTLY CERTAIN	COMPLETELY OR ALMOST COMPLETELY CERTAIN

HOW CERTAIN ARE YOU THAT…

1. Your partner's social network accepts you as their friend/family member's significant other
2. Your partner's social network approves of the fact that you and your partner are together
3. You partner's social network acts in a way that displays acceptance of you being in your partner's life
4. Your partner's social network purposefully interferes with your relationship
5. Your partner's social network thinks that you are "good enough" for your partner

HOW CERTAIN ARE YOU THAT…

1. Your partner's social network likes you
2. Your partner's social network enjoys spending time with you
3. Your partner's social network has invited you into their social circle
4. Your partner's social network wants to be friends with you
5. Your partner's social network would spend time with you even if your partner was not around

HOW CERTAIN ARE YOU THAT…

1. Your partner's social network does not make negative judgments about you you are as a person
2. Your partner's social network does not hold any of your insecurities against you
3. Your partner's social network does not talk about your behind your back
4. Your partner's social network does not constantly evaluate you

5. Your partner's social network treats you the way that you want to be treated

HOW CERTAIN ARE YOU THAT…

1. Your partner does not have a romantic connection with any of their social network members
2. Your partner does not have a physical relationship with any of their social network members
3. Your partner's social network members do not encourage them to cheat on you
4. Your partner prioritizes you over their social network
5. Your partner's social network does not threaten your relationship in any way

As you read the items below, please consider ONLY your partner interacting with **your social network** (close friends, family members, peers/coworkers, etc.). As you think about past, current, and future interactions between your partner and your social network, indicate your current level of CERTAINTY about the following statements (*1 = COMPLETELY OR ALMOST COMPLETELY UNCERTAIN; 7 = COMPLETELY OR ALMOST COMPLETELY UNCERTAIN*).

1	2	3	4	5	6	7
COMPLETELY OR ALMOST COMPLETELY UNCERTAIN	MOSTLY UNCERTAIN	SOMEWHAT UNCERTAIN	NEUTRAL	SOMEWHAT CERTAIN	MOSTLY CERTAIN	COMPLETELY OR ALMOST COMPLETELY CERTAIN

HOW CERTAIN ARE YOU THAT…

1. Your social network accepts your partner as your significant other
2. Your social network approves of the fact that you are with your current partner
3. You social network acts in a way that displays acceptance of your partner being in your life
4. Your social network might purposefully interfere with your relationship
5. Your social network thinks that your partner is "good enough" for you

HOW CERTAIN ARE YOU THAT…

1. Your social network likes your partner
2. Your social network enjoys spending time with your partner
3. Your social network has welcomed your partner into your social circle
4. Your social network wants to be friends with your partner
5. Your social network would spend time with your partner even if you were not around

HOW CERTAIN ARE YOU THAT…

1. Your partner is not jealous of the relationship that you have with any of your social network members
2. Your partner trusts you not to cheat on them with anyone from your social network
3. Your partner has no problem with you hanging around any of your social network members when you are not around
4. Your partner does not feel threatened by any of your network members
5. Your partner does not get angry when you spend time with your social network members

HOW CERTAIN ARE YOU THAT…

1. You can balance spending time with your partner vs. spending time with your social network
2. You can pay attention to the needs of your partner as well as the members of your social network
3. You never have to "choose" between your partner or your network members
4. The amount of time that you spend with your partner does not influence the relationship(s) you have with your social network
5. The amount of time that you spend with your social network member(s) does not influence the relationship that you have with your partner

HOW CERTAIN ARE YOU THAT…

36. Your partner and social network behave appropriately around each other
37. Your partner and social network are sensitive to each other's personalities
38. Your partner and social network members do not unfairly judge each other
39. Your partner and social network members respect one another
40. Your partner and social network members do not offend one another

*Note. Bolded items were removed from analysis during EFA.

IV. Partner Interdependence

In this next section, we are interested in understanding the ways in which the relationship that you share with the person in question affects your every day behavior. Said differently, we are curious about the ways that this relational partner influences your everyday behavior. On the scale below please indicate the degree to which you AGREE OR DISAGREE with the below prompts (1 = STRONGLY DISAGREE 7 = STRONGLY AGREE)

1	2	3	4	5	6	7
STRONGLY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	STRONGLY AGREE

1. This person influences the amount of time I spend with my friends
2. **I am very committed to maintain this relationship**
3. This person interferes with whether I achieve the everyday goals I set for myself
4. This person helps me in my efforts to make plans
5. **This relationship is very important to me**
6. **I would make a great effort to maintain my relationship with this person**
7. This person influences how much time I devote to my school work
8. This person interferes with the amount of time I spend with my friends
9. This person helps me to do the things I need to do each day
10. **I do not expect this relationship to last very long**
11. This person influences whether I achieve the everyday goals I set for myself
12. This person interferes with my ability to use my time well
13. This person helps me in my efforts to spend time with my friends
14. **I would like this relationship to last a lifetime**
15. **I am attached to my partner**
16. **I am committed to my relationship**
17. This person influences my ability to use my time well
18. This person interferes with how much time I devote to my school/work
19. This person helps me to achieve the everyday goals I set for myself
20. **I am likely to end my relationship in the near future**
21. This person influences whether I do the things I need to do each day
22. This person interferes with the things I need to do each day
23. This person helps me to use my time well

*Note. Bolded items were removed from analysis during EFA.

V. Network Interdependence

In this next section, we are interested in understanding the ways in which the relationship(s) that you share with your social network members affects your every day behavior. Said differently, we are curious about the ways that your social network influences your everyday behavior. On the scale below please indicate the degree to which you AGREE OR DISAGREE with the below prompts (1 = STRONGLY DISAGREE 7 = STRONGLY AGREE)

1	2	3	4	5	6	7
STRONGLY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	STRONGLY AGREE

1. My social network influences the amount of time I spend with romantic partner
2. I am very committed to maintaining my social network relationships
3. My social network interferes with whether I achieve the everyday goals I set for myself
4. My social network helps me in my efforts to make plans
5. My social network is very important to me
6. I would make a great effort to maintain my relationship my social network
7. My social network influences how much time I devote to school/work
8. My social network interferes with the amount of time I spend with my romantic partner
9. My social network helps me to do the things I need to do each day
10. I do not expect my relationships with my current social network members to last very long
11. My social network influences whether I achieve the everyday goals I set for myself
12. My social network interferes with my ability to use my time well
13. My social network helps me in my efforts to spend time with my romantic partner
14. I would like my social network relationships to last a lifetime
15. I am attached to my social network
16. I am committed to my social network
17. My social network influences my ability to use my time well
18. My social network interferes with how much time I devote to school/work
19. My social network helps me to achieve the everyday goals I set for myself
20. I am likely to end my social network relationship(s) in the near future
21. My social network influences whether I do the things I need to do each day
22. My social network interferes with the things I need to do each day
23. My social network helps me to use my time well

*Note. Bolded items were removed from analysis during EFA.

VI. Perceptions of Relational Talk as Threatening

In the next section we wish to observe the level of comfort that you have in talking with your current partner (the person whom you have referred to in previous questions) about the nature of your relationship. Said differently, we wish to see how threatening you perceive meaningful conversations about your relationship to be. On the scale below please indicate the degree to which you AGREE OR DISAGREE with the below prompts (1 = STRONGLY DISAGREE 7 = STRONGLY AGREE)

1	2	3	4	5	6	7
STRONGLY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	STRONGLY AGREE

HAVING A CONVERSATION ABOUT THE NATURE OF THIS RELATIONSHIP WOULD…

1. Threaten the relationship
2. Be embarrassing for me
3. Have a negative effect on the relationship
4. Make me feel vulnerable
5. Damage the relationship.

VII. Negative Emotions

In this next section, we are interested in your current emotional state regarding your relationship. Please consider how your partner makes you feel when you think about the relationship that you have with him/her. For the following questions, please indicate the extent to which you agree with the following statements (1 = STRONGLY DISAGREE 7 = STRONGLY AGREE)

1	2	3	4	5	6	7
STRONGLY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	STRONGLY AGREE

WHEN I THINK ABOUT MY RELATIONSHIP I FEEL…

1. Angry
2. Sad
3. Scared
4. Annoyed
5. Dreary
6. Fearful
7. Irritated
8. Dismal
9. Afraid

VIII. Enacted Relational Talk

In this next section we are interested in the amount of relationship-focused communication you have had with your current partner in the last week. Using the scales below please indicate the amount that you have avoided or discussed following topics (1 = ACTIVELY AVOIDED, 7 = ACTIVELY DISCUSSED).

1	2	3	4	5	6	7
ACTIVELY AVOIDED	AVOIDED	SOMEWHAT AVOIDED	NEUTRAL	SOMEWHAT DISCUSSED	DISCUSSED	ACTIVELY DISCUSSED

DURING THE PAST WEEK, WE HAVE ACTIVELY AVOIDED OR ACTIVELY DISCUSSED...
1. Our view of this relationship
2. Our feelings for each other
3. The future of the relationship

IX. Valence of Relational Talk

Considering your answers to the above questions, please indicate how positive or negative your relationship-focused conversations are. Using the scales below please indicate the positivity or negativity of each kind of conversation (1 = HIGHLY NEGATIVE, 7 = HIGHLY POSITIVE). If in the above questions you noted that you never have discussions with your partner, please check the box that says, "My partner and I have never had a conversation about this topic."

1	2	3	4	5	6	7
HIGHLY NEGATIVE	NEGATIVE	SOMEWHAT NEGATIVE	NEUTRAL	SOMEWHAT POSITIVE	POSITIVE	HIGHLY POSITIVE

WE HAD A POSITIVE/NEGATIVE CONVERSATION ABOUT…

1. Our view of this relationship
   - My partner and I have never had a conversation about this topic
2. Our feelings for each other
   - My partner and I have never had a conversation about this topic
3. The future of the relationship
   - My partner and I have never had a conversation about this topic

X. Perceptions of Turbulence

For the next section, we are interested in better understanding some of the ways in which you classify the relationship that you are currently in. Please indicate how much you DISAGREE OR AGREE with each item (1 = STRONGLY DISAGREE 7 = STRONGLY AGREE)

AT THE PRESENT TIME, THIS RELATIONSHIP IS…

1. exciting
2. chaotic
3. turbulent
4. in turmoil
5. exhilarating
6. tumultuous
7. hectic
8. frenzied
9. thrilling
10. overwhelming
11. stressful

*Note. Bolded items were removed from analysis during EFA.

APPENDIX B

FULL CORRELATIONS BETWEEN ALL MEASURED VARIABLES IN THIS STUDY

Measures	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Network-to-self acceptance	---	.54**	.42**	.49**	.43**	.15	-.10	.15	-.36**	.33*	.27**	-.16	-.24**
2. Judging		---	.29**	.42**	.41**	.07	-.27**	.09	-.41**	.12	.13	-.19*	-.16**
3.Third Party Threat			---	.31**	.50**	.28**	.06	.29**	-.24**	.37*	.37**	-.13	.-32**
4.Netwokr-to-partner acceptance				---	.48**	.05	-.21**	.18	-.42**	.32*	.32**	-.24**	.-27**
5. Jealous/Time Split					---	.30**	0.01	.41**	-.35**	.38*	.38**	-.16	-.28**
6. Network Interference						---	.55**	.65**	.15	.47**	.45**	.12	-.09
7. Network Facilitation							---	.30**	.41**	-.18	-.17	.18	.03
8.Partner Interference								---	-.04	.42**	.50**	.01	-.20**
9.Partner Facilitation									---	.19*	.21*	.38**	.35**
10. Rel. Talk as Threat										---	.30**	.28**	.41**
11. Negative Emotion											---	-.24**	-.30**
12. Enacted Relational Talk												---	.12
13. Relational Talk Valence													---

Note. *$p < .01$, **$p < .001$