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Exploring the Predictive and Theoretical Validity of the Network Interdependence Measure

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ABSTRACT
This study used measures of social network interference and facilitation to add to the heuristic value of relational turbulence theory. This manuscript advances theory and the value of network interdependence measures by relating them to measures of partner interdependence, as well as measures of negative emotions. Longitudinal results revealed that time 1 network interference predicted time 2 partner interference. Moreover, time 1 partner facilitation predicted time 2 network facilitation. Competing mediated models revealed that time 2 partner interference mediates the relationship between time 1 network interference and time 2 negative emotions. Time 2 network interference partially mediated the relationship between time 1 partner interference and time 2 negative emotions. Results are discussed in terms of theoretical, conceptual, and statistical value.

KEYWORDS
Interdependence; social networks; relational turbulence theory

Exploring the Predictive and Theoretical Validity of the Network Interdependence Measure Extant research across a variety of disciplines positioned a couple's social network(s) as vital to the quality and persistence of their relationship (Coromina, Guia, Coenders, & Ferligoj, 2008; Fiori et al., 2017; Sprecher, 2011). Theories of communication, however, remain primarily centered on dyadic interaction (e.g., Floyd, 2002; Petronio, 2010; Solomon, Knobloch, Theiss, & McLaren, 2016). That is, for many communication theorists, interactions and perceptions pertaining to a person/couple's social network(s) are thought of as outcomes of dyadic communication, rather than antecedents. An exception to this trend occurs in theories of social support (Keneski, Neff, & Loving, 2018). Thus, there are likely additional contexts in which social network perceptions precede dyadic perceptions. One such example is in the study of interdependence (Berscheid, 1983; Surra, 1988).

Foundational scholarship linked perceptions of interdependence in social networks to dyadic communication (Parks & Adelman, 1983; Parks, Stan, & Eggert, 1983; Sprecher & Felmlee, 2000). The causal functions of social network interdependence in relationship progression are largely ignored within interpersonal communication theories. This gap is important because close relationships do not occur within a vacuum (Felmlee, 2001). Social network perceptions may play pivotal roles in a variety of interpersonal communication theories.

One theory that can benefit from incorporating perceptions of social network interdependence is relational turbulence theory (RTT; Solomon et al., 2016). The goal of this manuscript is to include a measure of social network-based interdependence (i.e., network interdependence; Stein, 2018) as a theoretical component of relational turbulence theory. This manuscript will provide a short explanation of a) RTT's tenets, b) the role that network interdependence may play in RTT, and c) a longitudinal test in which network interdependence serves as a predictive indicator of several RTT variables.

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The mechanisms of RTT

Over time, turbulence scholarship shifted from the analysis of associative relationships (models of relational turbulence) to predicting causal outcomes based on generative mechanisms (RTT). The relational turbulence model (RTM) explained that perceptions of partner interdependence (facilitating and interfering behaviors from the partner) peak at moderate levels of intimacy (as do perceptions of social network involvement; Knobloch & Donovan-Kicken, 2006). Later iterations of the RTM proposed that major relational transitions were the pretext for heightened levels of perceived interdependence (Knobloch & Theiss, 2010; Knobloch & Theiss, 2011). Turbulence theory does not assume that levels of partner interdependence are inherently elevated by circumstance or other variables, in part, because studying turbulence through the limited scope of transitions "defies straightforward demarcation and falsifiability" (Solomon et al., 2016, p. 510). Thus, in RTT, perceptions of interdependence are considered a causal, exogenous mechanism. We adopted this theoretical structure in our study.

In RTT, interdependence is conceptualized using Berscheid's (1983) notion of interchain sequences – a causal chain of events in a person's life. Interdependence is the degree to which two people interrupt each other's interchain sequences. Interruptions can occur from facilitating or interfering behaviors. As measured variables, interference (the hindering of goals and activities) and facilitation (aiding in goal completion) gauge how much individuals believe their partners interrupt their everyday goals and activities (Knobloch & Solomon, 2004).

Perceptions of interdependence are said to heighten emotional reactions in close relationships, and thus, occur during the inception of the turbulence process (Solomon et al., 2016). Knobloch (2007) demonstrated that perceptions of interference can result in heightened senses of relational turmoil. Depressive symptoms (Knobloch & Theiss, 2011), hurtful experiences (McLaren, 2008), and increased anger (Knobloch & Theiss, 2010) also share associations with perceived interference from partners. Most importantly, hindering and helping behaviors from network members are strongly related to perceptions of partner inference and facilitation, respectively (Knobloch & Donovan-Kicken, 2006).

As evidenced by the above literature, interdependence is not confined to romantic relationships by Berscheid's (1983) or RTT's (Solomon et al., 2016) standards. Partnerships preclude high levels of interdependence (Rusbult, Arriaga, & Agnew, 2003); however, interdependent relationships can extend to family, friends, coworkers, and others (Leenders, 2013). Given the strong link between perceptions of interference/facilitation from partners and network hindering/helping behaviors (Knobloch & Donovan-Kicken, 2006), there is reason to believe that perceptions of network involvement (e.g., network interdependence, Stein, 2018) can contribute to the turbulence process. Interpersonal literature previously documented how network perceptions correlate with relationship quality (Parks et al., 1983; Sprecher, 2011). We discuss some findings of note below.

How social networks influence close relationships

Considerable research described the influence a couple's social networks can have on 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. As such, the characteristics, qualities, and results of social network interdependence are worth discussing.

Social network characteristics and behaviors

Scholars have offered competing definitions as to what constitutes a person's social network (Agnew et al., 2001; Sprecher, 2011; Surra, 1988). Research has identified the two most common attributes of a social network as a desire for continued interaction and an overall affinity for group members (Hill

& Dunbar, 2003). Participants often describe network members as "kin" with whom they are close (e.g., Parks et al., 1983). When Sprecher (2011) asked participants to report on a "network member," friends were the predominant choice, followed by family. That said, social networks could also contain co-workers, peers, and neighbors (Hill & Dunbar, 2003).

Like dyads, social networks (and the individuals in them) are interdependent. Surra (1988) 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). It may be that dense clusters of reachable network members who overlap with one another are likely interdependent and, therefore, have the ability to interfere with and facilitate each other's daily goals. As two (or more) individuals become more interdependent, levels of interference and facilitation increase between these individuals (Berscheid, 1983). These perceptions and behaviors may influence the romantic relationships for network members.

Network influence on relationship satisfaction and quality

Perhaps due in part to network interdependence, social network members can influence relational outcomes in several ways. Members of networks will intentionally hinder a relationship that they do not support (Sprecher, 2011; Surra, 1990). Network members also aid in the development of relationships perceived as more successful and intimate (Knobloch & Donovan-Kicken, 2006). This implies that network members see themselves as capable of altering the perceptions that occur within a dyadic relationship (Sprecher, 2011), even if the members of the couple do not.

Several studies explored the ways in which sources of network interdependence (see Surra, 1988) produce relational outcomes. Agnew et al. (2001) reported positive relationships between network overlap and levels of couple commitment, investment, and relationship satisfaction. Additionally, closeness (for women) and insecurity (for men) toward one's own network (i.e., network density) positively relate to dyadic closeness (Neyer & Voigt, 2004). Network size facilitates engagement in romantic relationships for adolescents (Connolly & Johnson, 1996). Thus, the characteristics of Surra's network interdependence suggest that interfering and facilitating behaviors occur within networks.

Defining and measuring network interdependence

The above studies imply that 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 negative emotions. To operationalize this phenomenon, Stein (2018) developed measures of network interference and facilitation, described below.

The notion of network interdependence stems from the conceptualization derived by Berscheid (1983) as opposed to characterizations described by Surra (1988). Network interdependence, from an interpersonal standpoint, can be understood as "the degree to which members of a social network influence the goals of individuals in that network" (Stein, 2018, p. 2). Network interference is the extent to which a person's network disrupts his/her daily goals, and network facilitation is the extent to which a person's network helps its members accomplish everyday goals.

Using exploratory and confirmatory factor analyses, Stein (2018) developed measures of network interference and facilitation. Tests of convergent and divergent validity demonstrated that network interference and facilitation correlate with turbulence variables in the same manner as partner interference/facilitation; however, no tests of predictive or theoretical viability was produced. The

goal of this manuscript is to use longitudinal data to test the predictive validity of network interference and facilitation. These tests will be couched within the framework of RTT, the theory from which the measurement was developed.

Hypotheses and research questions

The theoretical goal of this manuscript is to test how, if at all, network interdependence contributes to the turbulence process. By Berscheid's (1983) categorization of interdependence, there are three potential roles that network interdependence can play vis-à-vis partner interdependence (Knobloch & Solomon, 2004) and its outcomes – heightened emotional reactions (Solomon et al., 2016). It may be that a) network and/or partner interdependence influence emotional reactions directly, b) network and/or partner interdependence influence emotional reactions indirectly, or c) there are simultaneous direct and indirect effects between network interference, partner interference, and emotional reactions. We discuss these three possibilities in two sets of hypotheses and research questions.

It is possible that perceptions of network interdependence are antecedent to perceptions of partner interdependence and/or emotional reactions. Previous studies have positioned network perceptions as affecting dyadic evaluations (see Parks et al., 1983; Sprecher & Felmlee, 2000). In this scenario, time 1 measures of network interference and facilitation would predict time 2 measures of partner interference and facilitation, respectively. Moreover, there could be both direct and indirect associations between time 1 measures of network interference/facilitation and time 2 measures of emotional reactions, mediated by time 2 measures of partner interference and/or facilitation. Turbulence scholars demonstrated that partner interference can serve as a mediating factor between variables (Knobloch, 2007; Knobloch & Donovan-Kicken, 2006; Knobloch, Miller, & Carpenter, 2007). We consider the notion that perceptions of network interdependence relate to emotional outcomes, either independent from or through perceptions of partner interdependence in our first hypothesis and research question.

H1a: Time 1 measures of network interference are positively related to time 2 measures of partner interference.

H1b: Time 1 measures of network facilitation are positively related to time 2 measures of partner facilitation.

RQ1: How do time 1 measures of network interference and facilitation relate to time 2 measures of emotion through time 2 measures of partner interference and/or facilitation?

It may also be that time 1 measures of partner interference and facilitation predict time 2 measures of network interference and facilitation, respectively. Conceptually, this is in line with Berscheid's (1983) definition of interchain sequences, which allows for the meshing of multiples goal structures. The extent of a couple's meshed interchain sequence may in turn influence the amount of sequence-overlap that partners have with their respective networks (as well as their shared, duocentric network; Coromina et al., 2008).

According to turbulence scholars, partner interdependence can directly (Solomon et al., 2016), or indirectly relate to outcome variables (see McLaren, 2008). The relationship between partner interdependence and emotional reactions may be modulated by intervening variables. Thus, there may be both direct and indirect associations for partner interference/facilitation at time 1 and heightened emotions at time 2, mediated by time 2 measures of network interference and/or facilitation. The second hypothesis and research question account for this possibility.

H2a: Time 1 measures of partner interference are positively related to time 2 measures of network interference.

H2b: Time 1 measures of partner facilitation are positively related to time 2 measures of network facilitation.

RQ2: How do time 1 measures of partner interference and facilitation relate to time 2 measures of emotion through time 2 measures of network interference and facilitation?

Method

Participants and procedures

Two waves of data were collected from 333 adults (178 men) using Amazon's Mechanical Turk (i.e., MTurk). Mechanical Turk was chosen for this study due to participants' diverse demographics (Paolacci & Chandler, 2014) and high level of reliability (for both mortality and response rate; Peer, Vosgerau, & Acquisti, 2014). Respondents received $1.50 for each wave of the survey about interpersonal relationships. Qualifications for participation included a minimum age of 18, internet access, and current status in a romantic and/or sexual relationship of some kind. Following qualification, respondents were guided through a series of Likert-style questions aimed to measure each of the variables of interest. Data were collected six weeks apart, featuring a mortality rate of 50.20% (wave 1 included 642 participants).[1]

Participants' ages ranged from 20–74 (M = 36.07, SD = 9.97). The average relationship length was 5.75 years (SD = 4.37). Most respondents identified as heterosexual (n = 303); however, a number of participants identified as bisexual (n = 23) and homosexual (n = 7). People identified as being married (or in a civil union; n = 174) or in a serious dating relationship (n = 102). Less common relationship types included casual daters (n = 38) and engaged to be married (n = 19). The ethnicity of the sample was Caucasian (n = 194), followed by Asian (n = 71), Indian (n = 31), African American (n = 17) and Hispanic/Latinx (n = 11). Five individuals reported as being "mixed race," two reported as Native Americans and one as a Pacific Islander.

Measures

Network interdependence

Stein's (2018) measure of network interference and facilitation was used in this study.[2] 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 at time 1; α = .91 at time 2) and *facilitation* (α = .89 at time 1; α = .92 at time 2) were all deemed reliable. For this scale, 1 = *strongly disagree* and 7 = *strongly agree*. High scores reflected greater levels of network interdependence.

Partner interdependence

Knobloch and Solomon (2004) partner influence scale measured perceptions of interference and facilitation. Participants indicated their agreement with 10 items on a seven-interval Likert scale (e.g., *my social network makes it hard for me to complete my daily tasks; my social network helps me with my school/work*). Subscales measuring a partner's interference (α = .93 at time 1; α = .95 at time 2) and facilitation (α = .89 at time 1; α = .92 at time 2) were all deemed reliable. For this scale, 1 = *strongly disagree* and 7 = *strongly agree*. High scores reflected greater levels of partner interdependence.

Negative emotions

Dillard, Kinney, and Cruz (1996) emotions in close relationships scale was used in this study. Participants indicated their agreement on a seven-point Likert scale 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"). Importantly, all nine items factored into a single, unidimensional scale during factor analysis. For this measure, 1 = and *strongly disagree*; 7 = *strongly agree*. This measurement was deemed reliable at time 1 (α = .96) and time 2 (α = .91). High scores reflected greater levels of negative emotions.

Results

Four distinct models were run using SPSS and AMOS to test the hypotheses and research questions. Structural equation modeling (i.e., path analysis) was run to test the longitudinal relationships between variables of interest.[3] In the first model (H1), time 1 network interference and facilitation are positioned as independent variables, and time 2 measures of partner interference and facilitation are considered as dependent variables. The second model (H2) is the obverse, in that time 1 measures of partner interference and facilitation are used as independent variables, and time 2 measures of network interference and facilitation are dependent variables. These exploratory tests were performed to see which of these two models displays the best fit, and which model explains the most variation in dependent variables.

The final two models include measures of negative emotion as a dependent variable. The third model (RQ1) tests time 1 network interference and facilitation as independent variables, and time 2 partner interference and facilitation as mediating variables. The fourth model (RQ2) observes time 1 partner interference and facilitation as independent variables and time 2 network interference and facilitation as mediating variables. Correlations between all measured variables can be seen in Table 1. Throughout the analyses, we controlled for scores on the dependent variables at time 1 by including them in the model with paths to the dependent variables at time 2 (Collins, Schafer, & Kam, 2001).

During analyses, several fit indices were implemented: the χ^2/df, with values under 3.0 indicating excellent fit (Schumacker & Lomax, 2010); the comparative fit index (CFI) with values at or above .95 indicating excellent fit (Hu & Bentler, 1995, 1999); the Root Mean Square Error of Approximation (RMSEA) with values under .06 indicating excellent fit (Browne & Cudek, 1993; Hu & Bentler, 1999); and the Standardized Root Mean Square Residual (SMRS) with values under .08 indicating good fit (Hu & Bentler, 1999). Standardized regression weights (i.e., β) tested the strength of path relationships, and multiple squared correlations (i.e., R^2) were assessed to determine explained variance. Preacher and Hayes (2008) bootstrapping method was used to test mediated paths in which total, direct, and indirect regression weights are used to determine partially or fully mediated paths. Prior to substantive analyses, CFA and measurement models for each hypothesis were tested. In all cases, models displayed excellent fit. It was therefore deemed appropriate to proceed with path analyses.

Table 1. Bivariate correlations for all measured variables in this study.

Variable	Part. Int. 1	Part. Int. 2	Part. Fac. 1	Part. Fac. 2	Net. Int. 1	Net. Int. 2	Net. Fac. 1	Net. Fac. 2	Neg. Emo. 2
Part. Int 1	–								
Part. Int. 2	.73**	–							
Part. Fac. 1	.04	.04	–						
Part. Fac. 2	.02	.05	.69**	–					
Net. Int. 1	.70**	.65**	.21*	.15*	–				
Net. Int. 2	.63**	.70**	.18*	.19*	.81**	–			
Net. Fac. 1	.35**	.32**	.45**	.35**	.56**	.47**	–		
Net. Fac. 2	.33**	.41**	.42**	.43**	.48**	.59**	.68**	–	
Neg. Emo. 2	.41**	.48**	–.10	–.11	.43**	.47**	.22**	.27**	–
M	3.55	3.42	4.99	4.96	3.09	3.09	5.00	4.19	2.04
SD	1.60	1.78	1.22	1.31	1.78	1.75	1.45	1.43	1.52

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

Table 2. Test for mediation using bootstrapping method. Unstandardized effects for total, direct, and indirect effects.

			Total effect		Direct effect		Indirect effect		
IV	DV	MV	Estimate	SE	Estimate	SE	Estimate	SE	95% CI
NI1	EM2	PI2	.11**	.07	.01	.04	.10**	.07	[.18, .01]
NI1	EM2	PF2	.01	.06	.01	.05	<.01	.03	[.09, −.08]
]NF1	EM2	PI2	−.04	.06	<.01	.05	−.04	.05	[.14, −.06]
]NF1	EM2	PF2	.05	.06	.06	.05	−.01	.05	[.13, −.04]

Note. NI1 = network interference at time one; NF1 = network facilitation at time 1; PI2 = partner interference at time 2; PF2 = partner facilitation at time 2; EM2 = negative emotions at time 2. *p < .05, **p < .01. All values in this table are unstandardized. Results demonstrate that time 2 partner interference fully mediates the relationship between time 1 network interference and time 2 negative emotions.

Table 3. Test for mediation using bootstrapping method. Unstandardized effects for total, direct, and indirect effects.

			Total effect		Direct effect		Indirect effect		
IV	DV	MV	Estimate	SE	Estimate	SE	Estimate	SE	95% CI
PI1	EM2	NI2	.24**	.07	.13**	.03	.11**	.03	[.29, .05]
PI1	EM2	NF2	.12	.07	.11**	.05	.01	.03	[.21, .03]
PF1	EM2	NI2	.05	.07	.04	.05	−.01	.04	[.03, −.04]
PF1	EM2	NF2	.06	.07	.06	.04	<.01	.04	[.16, −.04]

Note. NI1 = network interference at time one; NF1 = network facilitation at time 1; PI2 = partner interference at time 2; PF2 = partner facilitation at time 2; EM2 = negative emotions at time 2. *p < .05, **p < .01. All values in this table are unstandardized. Results demonstrate that time 2 network interference fully mediates the relationship between time 1 partner interference and time 2 negative emotions.

Model 1 – network interdependence predicting partner interdependence

The first model tested the longitudinal relationships between time 1 measures of network interdependence time 2 measures of partner interdependence. Results of this model demonstrated excellent fit (see Figure 1). Time 1 network interference (β = .28) was statistically and positively related to time 2 partner interference, (R^2 = .05, p = .02). Time 1 network facilitation (β = −.03) was not significantly related to time 2 partner interference. Neither time 1 network interference (β = −.02) or network facilitation (β = .03) were significantly related to time 2 partner facilitation.

Model 2 – partner interdependence predicting network interdependence

The second model tested the longitudinal relationship between measures of time 1 partner interdependence time 2 measures of network interdependence. Results of this model demonstrated good-to-excellent fit (see Figure 2). Time 1 partner facilitation (β = .14) was significantly and positively related to time 2 network facilitation (R^2 = .04, p = .03). Time 1 partner interference (β = .02) was not significantly related to time 3 network facilitation. Neither time 1 partner interference (β = .09) or time 1 partner facilitation (β = .01) was significantly related to time 2 network interference (R^2 = .03).

Model 3 – partner interdependence as a mediating variable

The third model positioned time 1 measures of network interference and facilitation as predictor variables of time 2 negative emotion with time 2 measures of partner interference and facilitation as mediating variables. Results of this model demonstrated good-to-excellent fit (see Figure 3).[4] The independent and mediating variables accounted for 32% of the variation in the dependent variable (i.e., R^2 = .32). Time 2 partner interference (β = .17) shared a significant direct relationship to time 2 negative emotions and fully mediated the indirect relationship between time 1 network interference and time 2 negative emotion (β = .10).

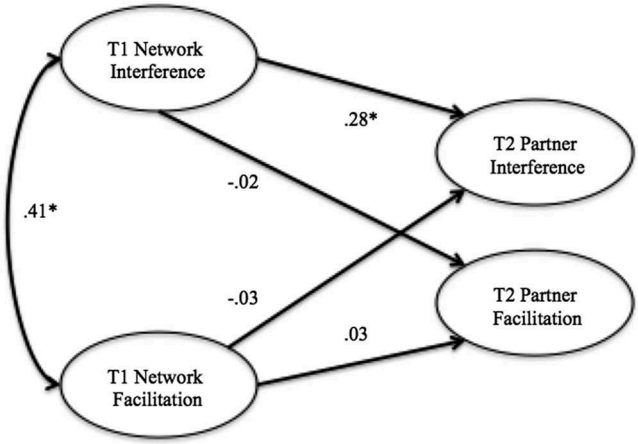

Figure 1. Associations between time 1 network interdependence and time 2 partner interdependence.

Note. *$p < .001$. $\chi^2 = (390) = 795.87$ ($p < .001$), $\chi^2/df = 2.04$; CFI = .95; RMSEA = .056 (95% CI: .049 - .061); and SRMR = .064. All regression weights shown in this model are standardized. Time 1 measures of partner interdependence and relationship length are controlled for, but not shown in this model. R^2 = .05 and .02 for partner interference and facilitation, respectively.

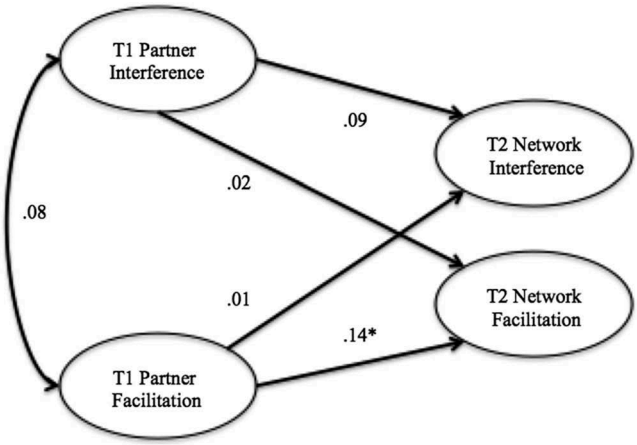

Figure 2. Associations between time 1 partner interdependence and time 2 network interdependence.

Note. *$p > .01$. $\chi^2 = (390) = 804.62$ ($p < .001$), $\chi^2/df = 2.06$; CFI = .95; RMSEA = .058 (95% CI: .046 - .063); and SRMR = .058 All regression weights shown in this model are standardized. Time 1 measures of network interdependence and relationship length are controlled for, but not shown in this model. R^2 = .05 and .02 for network interference and facilitation, respectively.

Model 4 – network interdependence as a mediating variable

The final model positioned time 1 measures of partner interference and facilitation as predictor variables of time 2 measures of negative emotion with time 2 measures of network interference and facilitation as mediating variables. Results of this model demonstrated good-to-excellent fit (see Figure 4). The independent and mediating variables accounted for 34% of variation in the dependent variable (i.e., R^2 = .34). Both time 1 partner interference (β = .14) and time 2 network interference (β = .24) shared a significant direct relationship with time 2 negative emotions. Time 2 network

interference partially mediated the indirect relationship between time 1 network interference and time 2 negative emotion (β = .11).

Discussion

The goal of this study was to test the theoretical and predictive validity of Stein's (2018) measure of network interdependence using RTT. Results of this study provide several theoretical, conceptual, and methodological developments as it pertains not only to the measure of network interdependence, but also to the tenets of RTT. We offer three implications for these results: RTT developments, the role of network interdependence, and model comparisons.

RTT developments

One noteworthy development in this study was the finding that partner interference and facilitation were not the sole indicators of heightened emotional reactions. As demonstrated by Figures 3 and 4, measures of negative emotion are both directly and indirectly influenced by the perception of network interference, but not network facilitation. As such, the relationship between partner interference/facilitation and heightened emotions may not be as clear (i.e., direct) as once thought. The role of network interdependence vis-à-vis partner interdependence and emotional arousal is in line with the theoretical reasoning of RTT. As noted in proposition two of RTT, facilitating and (more so) interfering interruptions heighten emotional arousal (Solomon et al., 2016). Our results supported that supposition; and illustrated a similar tendency for network interruptions. Moreover, as shown by Figures 1 and 2, the relationships between network and partner interdependence remain present, but unclear. Our findings are an initial suggestion that, perhaps, RTT could benefit from including measures of network-based variables as instigators of the turbulence process.

This study provides a bridge between the research on social network influence (e.g., Felmlee, 2001; Coromina et al., 2008; Sprecher, 2011) and the causal mechanisms of RTT. Turbulence theory

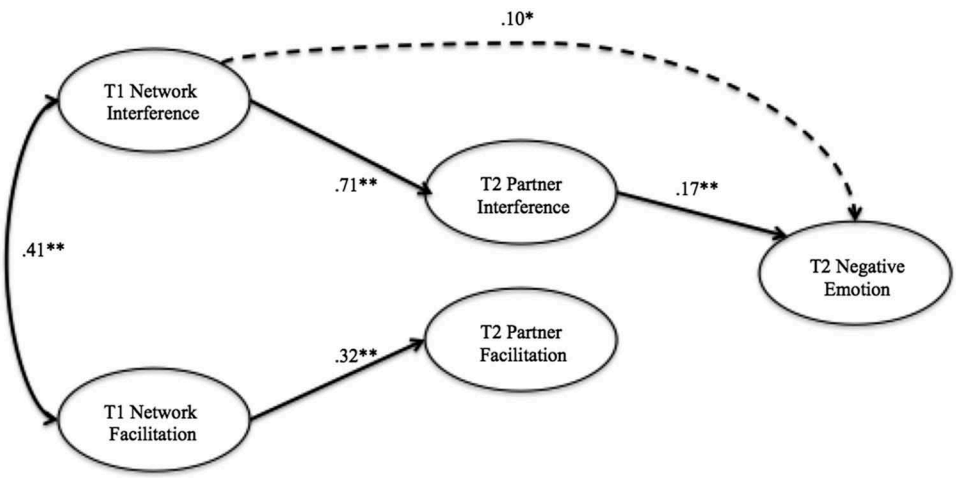

Figure 3. Associations between time 1 network interdependence and time 2 negative emotion (time 2 partner interdependence as a mediating variable).

Note. *p < .01, **p = .001. χ^2 = (612) = 1450.76 (p < .001), χ^2/df = 2.37; CFI = .93; RMSEA = .064 (95% CI: .058 - .068); and SRMR = .064. All regression weights shown in this model are standardized. Time 1 measures of negative emotion and relationship length were controlled for, but not shown in this model. R^2 = .70 for negative emotion (R^2 = .32 for independent and mediating variables). Dotted lines represent fully mediated paths. Only significant paths are shown in this model.

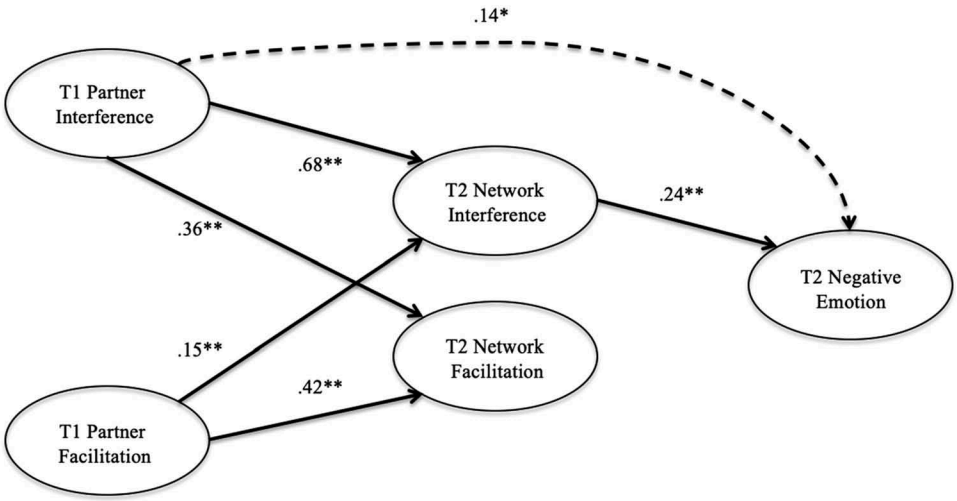

Figure 4. Associations between time 1 partner interdependence and time 2 negative emotion (time 2 network interdependence as a mediating variable).

Note. *p < .01, **p = .001. χ^2 = (613) = 1535.97 (p < .001), χ^2/df = 2.51; CFI = .93; RMSEA = .067 (95% CI: .060 - .069); and SRMR = .065 All regression weights shown in this model are standardized. Time 1 measures of negative emotion and relationship length were controlled for, but not shown in this model. R^2 = .71 for negative emotion (R^2 = .34 for independent and mediating variables). Dotted lines represent partially mediated paths. Only significant paths are shown in this model.

positions interaction with the network as an outcome of the turbulence process, rather than a potential cause. Specifically, Solomon et al. (2016) propose that "relational turbulence … constrains disclosures with social networks (p. 522)." The findings of this study suggest that network interactions may be both a cause and a result of relational turbulence. Thus, our results provide an initial contribution to both the development of RTT and the development of interpersonal communication theory.

The role of network interdependence

In addition to the theoretical contributions provided to RTT, it is also important to understand how network interdependence, as a measured variable, functions within the broader nomological network (Worthington & Whittaker, 2006). The most robust method is to use time-ordered association analyses as a method of forming causal arguments. Even six weeks apart, measures of network interference related to both partner interference and negative emotions. These results suggest that the network interdependence measure can contribute to multiple outlets of relationship research, rather than RTT.

Previous literature, as well as this study, has noted minimal correlations between partner interference and facilitation as measured variables (Knobloch et al., 2007). Network interference and facilitation, however, were strongly related to each other (see Figures 1 and 3). Berscheid (1983) explains that interdependence manifests through the interruption of everyday activities. When considering one's partner, helping behaviors (e.g., favors, dedication of time/resources), need not be intrinsically tied to interfering behaviors (e.g., plan construction, chores). When considering one's network members, positive and negative interruptions appear to be related (and perhaps even dependent upon) one another. Thus, it appears that the sources (Surra, 1988), content (Sprecher, 2011), and intercorrelations between elements of network interdependence are quite different from those of partner interdependence (Knobloch & Solomon, 2004).

One example of this branch of thought can be found in literature concerning the intentionality of interfering and facilitating behaviors. Sprecher (2011) explains that relational interference from the network is usually intentional. Interfering behaviors from a partner are typically unintentional (Nagy & Theiss, 2013). Thus, where RTT proposes that interference/facilitation from a partner heightens emotional arousal (Solomon et al., 2016), network interference/facilitation may directly influence outcomes such as a person's delegation of free time between network members and partners (Felmlee, 2001), romantic involvement (Parks et al., 1983), or, as shown by our results, perceptions of partner interference/facilitation.

To that end, it would appear as though network interdependence and partner interdependence are related to each other both conceptually and empirically. People consider the interdependence in their dyadic partnerships distinct from those in their social networks (Stein, 2018). We contend that a person's interchain sequence is interrupted not only by his/her partner, but also by the close relationships that exist outside of that dyad (initially demonstrated by Sprecher, 2011). This is evidenced by the mediating relationships displayed in Figures 3 and 4. In short, these findings are a first step toward arguing that extra-dyadic relationships can interrupt interchain sequences both independently from, and in tandem with, partner interruptions. Combined with early turbulence work linking partner interdependence to social network helping/hindering behaviors (Knobloch & Donovan-Kicken, 2006), our results call for future studies to further clarify the relationship between partner and network interdependence, especially through additional theoretical frameworks.

Model comparisons

One pressing question regarding network interdependence as a measured variable is where it should be placed in hierarchical models (i.e., an independent, dependent, or mediating variable). In this study no one model was a better fit than the others. This finding further articulates our earlier argument that network-dyadic interaction is dynamic, rather than static. Felmlee (2001) explains that it is common for interruptions from both a partner and a network to occur simultaneously in a person's life. Solomon et al. (2016) summarize that perceptions of interfering behaviors are more instrumental in heightening emotion than are facilitating behaviors. These arguments help explain Figures 3 and 4, and also suggest that network and partner interdependence act both individually and in tandem with each measure, serving as a partial and/or full mediator.

Figure 4 displayed the strongest regression weights. In this figure, time 2 measures of network interference partially mediated the relationship between time 1 measures of partner interference and time 2 measures of negative emotion. It appears that perceptions of partner interference are more resilient over time, as they relate to negative emotions. Moreover, the a-temporal association between network interference and negative emotion (see Figure 4) was stronger than that of partner interference (see Figure 3). Combined with the strong associations between time 1 measures of partner interdependence and time 2 measures of network interdependence, it is reasonable to conclude that Figure 4 is the most appropriate model.

The viability of Figure 4 runs counter to foundational work on social networks and relationship outcomes (see Parks et al., 1983; Sprecher & Felmlee, 1992), which suggests that perceptions of network involvement lead to perceptions of dyadic involvement, in turn influencing relational outcomes. Our results suggest that this process may work in reverse as well. Figures 3 and 4 displayed nearly identical R^2 values for time 2 measures of negative emotions. It is our suggestion that additional outcomes of network and partner interdependence be explored to determine how one set of measurements functions vis-à-vis the other.

Limitations and future directions

Despite the strengths in this study there are several limitations. Our methods could benefit from three developments. First, although longitudinal data is ideal for establishing causal relationships, the

addition of a third and fourth wave of collection would allow us to better observe the extent of the relationship(s) between network and partner interdependence, as well as illustrate a pattern of perceptions leading up to outcome variables. For example, in each model, all of our dependent variables were collected at the same point in time. Using additional waves of collection would aid in our understanding of the relationships between network interdependence, partner interdependence, negative emotions, and a host of other outcome variables. This pattern of cyclical events is at the heart of the turbulence process (Solomon et al., 2016), as well as Berscheid's (1983) conceptualization of interchain sequences.

Related, although RTT describes negative emotion as the most common result of increased interruptions from partners (Solomon et al., 2016), it is reasonable to assume that other emotional, cognitive, and behavioral outcomes could be the result of network interdependence, and partner interdependence. Future research should explore not only emotional reactions to one's romantic relationship, but also emotional reactions to one's network and the members within them. Other potential outcomes could include depressive symptoms, stress markers, and relational communication. Turbulence theory predicts that interfering and facilitating behaviors heighten emotional responses, but the usefulness of interdependence measures is not limited to one theory. Testing the tenets of theories such as communication privacy management (Petronio, 2010), communication accommodation (Gallois & Giles, 2015), and affection exchange (Floyd, 2002) may demonstrate further theoretical usefulness of not only measures of network interdependence, but also partner interdependence

Finally, the sample for this study was restricted in several ways. Although there was a suitable balance of ethnicities and races in this study, the overabundance of married couples is potentially problematic. Turbulence scholars have suggested that perceptions of interdependence are most impactful during the courtship stage of relationship development (Knobloch & Donovan-Kicken, 2006; Knobloch et al., 2007). Moreover, Stein (2018) demonstrated that measures of network interdependence function differently across multiple relationship types. It would be useful to explore the predictive validity of network interdependence in fledging relationships, as well as established partnerships. This manuscript provides a step in the development of social networks as causal role-players in relationship development and maintenance. Ideally, future research will compliment this work in a variety of settings and contexts.

Notes

1. A MANOVA concluded that responses did not statistically differ between participants who completed only time 1 questions and participants who completed time 1 and time 2 questions. A separate MANOVA showed nonsignificant results across relationship types for these same outcome variables. ($\eta^2 < .02$ in all cases).
2. Prior to answering social network related questions, participants were provided with a description of a social network as "people who you generally like and are close with, and who you spend time with regularly."
3. Prior to analyses, it was revealed that length of relationship correlated significantly with nearly every variable in this study. For this reason, relationship length was controlled for in all substantive analyses.
4. Note. After consultation of modification indices, two covariations were drawn between items in the latent variable negative emotion. One item was removed from this variable to decrease multicollinearity. These modifications also apply to the results of model 4.

Disclosure statement

No potential conflict of interest was reported by the author.

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