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**7 authors**, including:


Edward Orehek
University of Pittsburgh


Amy L Veenstra



Robin A Barry
University of Wyoming



Christopher A Abeare
University of Windsor

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# Forecasting the specific providers that recipients will perceive as unusually supportive

AMY L. VEENSTRA,[a,b] BRIAN LAKEY,[b] JAY L. COHEN,[c] LYNN C. NEELY,[c] EDWARD OREHEK,[d] ROBIN BARRY,[e] AND CHRISTOPHER A. ABEARE[f]

[a] *Wayne State University;* [b] *Grand Valley State University;* [c] *John D. Dingell VA Medical Center;* [d] *University of Groningen;* [e] *University of Maryland, Baltimore County;* [f] *University of Windsor*

## Abstract

Perceived support primarily reflects the relationships among specific recipients and providers. These strong relational influences suggest a new approach to interventions: Match specific providers with specific recipients so that unusually supportive relationships emerge. For this approach to be successful, progress must be made on several basic research questions. For example, it must be possible to forecast the specific providers that recipients will perceive as unusually supportive (i.e., forecasting relational support). In 2 studies, support recipients had 3 or 5 conversations with the same providers and reported affect, provider supportiveness, and perceived similarity (Study 2 only) after each conversation. Relational support could be forecasted from recipients' reactions to a single, brief conversation with each provider, even after 4 months had elapsed.

People with higher perceived support have better mental health than those with lower perceived support, including lower rates of major depression (Lakey & Cronin, 2008), fewer posttraumatic stress symptoms (Brewin, Andrews, & Valentine, 2000), less nonspecific psychological distress (Barrera, 1986; Cohen & Wills, 1985), and higher positive and lower negative affect (Finch, Okun, Pool, & Ruehlman, 1999). These findings suggest that social support research might yield new preventive interventions. Yet, randomized controlled trials of such interventions have yielded disappointing results (Helgeson & Gottlieb, 2000; Hogan, Linden, & Najarian, 2002; Lakey & Lutz, 1996). Drawing from a new theory of perceived support (relational regulation theory [RRT]; Lakey & Orehek, 2010), we hypothesize that the disappointing results occurred because researchers attempted to assign objectively supportive providers to recipients. RRT states that rather than reflecting providers' objective qualities, perceived support primarily reflects recipients' and providers' relationships (i.e., relational support; Lakey, 2010; Lakey, McCabe, Fisicaro, & Drew, 1996). RRT recommends new approaches to intervention whereby specific providers and recipients are matched so that unusually supportive relationships emerge. However, for relational interventions to be successful, progress must be made on a few basic research questions, including "What information do recipients use to judge provider supportiveness?" and "How early in an acquaintance can meaningful support judgments be made?" This article addresses these and other basic research questions.

Although some social support interventions have attempted to change existing relationships (Hogan et al., 2002), an important type of intervention has been to make available to

Amy L. Veenstra, Department of Psychology, Wayne State University; Amy L. Veenstra and Brian Lakey, Department of Psychology, Grand Valley State University; Jay L. Cohen and Lynn C. Neely, Psychology Section–Mental Health Service, John D. Dingell VA Medical Center; Edward Orehek, Department of Social and Organizational Psychology, University of Groningen; Robin Barry, Department of Psychology, University of Maryland, Baltimore County; Christopher A. Abeare, Department of Psychology, University of Windsor.

Correspondence should be addressed to Amy L. Veenstra, Wayne State University, e-mail: alveenstra@wayne.edu or Brian Lakey, Grand Valley State University, e-mail: lakeyb@gvsu.edu.

recipients support providers who are strangers to recipients initially. Although there have been some modest successes (Barrera, Glasgow, McKay, Boles & Feil, 2002; Weber et al., 2007), most controlled studies have yielded disappointing results (for reviews, see Helgeson & Gottlieb, 2000; Hogan et al., 2002; Lakey & Lutz, 1996). For example, Heller, Thompson, Trueba, Hogg, and Vlachos-Weber (1991) randomly assigned at-risk women to receive regular supportive phone calls. Yet, women who received supportive phone calls did not show greater improvements in perceived support or mental health compared to controls. Thoits, Hohmann, Harvey, and Fletcher (2000) assigned support providers to veterans who had recently undergone bypass surgery. Supported veterans did not show better outcomes than controls. In Helgeson, Cohen, Schultz, and Yasko (1999), women with breast cancer were randomly assigned to control, support groups, or education groups. Education groups benefited women's adjustment, but support groups did not.

These interventions' limited success has important theoretical implications because they were generated from the dominant theory of social support: stress and coping social support theory (S&CSST; Cohen & Wills, 1985; Cutrona & Russell, 1990; Thoits, 1986). S&CSST hypotheses that perceived support is linked to better mental health because specific supportive actions (e.g., advice or reassurance; i.e., enacted support) protect recipients from the harmful effects of stress (i.e., stress buffering) by promoting more adaptive coping and appraisals. Perceived support reflects a history of receiving effective enacted support. Furthermore, some supportive actions are objectively more supportive than other actions in certain situations (Cohen & Hoberman, 1983; Cutrona & Russell, 1990). S&CSST is commonly interpreted to state that some support providers are more objectively supportive than other providers, although the theory is not explicit on this point.

The studies presented here were guided by RRT (Lakey & Orehek, 2010). RRT states that there is little in the way of objectively supportive actions or providers, and that instead who and what is supportive is primarily relational (i.e., reflects the personal tastes of recipients). RRT was developed to explain the main effect (Cohen & Wills, 1985) between perceived support and mental health, and thus RRT does not rely upon appraisal, coping, or stress buffering as explanatory mechanisms. Instead, RRT hypothesizes that social interaction regulates recipients' affect through ordinary, day-to-day conversations, and shared activities (cf. Thoits, 1985). According to RRT, each person has largely idiosyncratic patterns of affective responses to other people and things (e.g., animals, activities, ideas, objects, and symbolic people such as celebrities). When recipients and providers are well matched, conversation regulates affect because recipients and providers talk about other people and things in a way that elicits favorable emotion(s) in both recipients and providers. The main effect between perceived support and mental health emerges from such conversations and shared activities, regardless of the presence of stress or whether stress and coping is discussed.

RRT suggests hypotheses about why previous interventions have not been optimally effective, how interventions could be designed differently, and basic research questions that must be addressed before RRT's recommended interventions can be successful. RRT hypothesizes that previous interventions have not been optimally effective because they have been guided by an implicit assumption that there are objectively supportive providers. As just described, RRT states that perceived support is primarily relational. Thus, interventions will be more successful if specific providers were made available to specific recipients such that unusually supportive relationships emerged. For such interventions to be successful, progress must be made on a few basic research questions. Foremost, is it possible to forecast which providers will be unusually supportive to which recipients? Such forecasting requires progress on other basic research questions. For example, forecasting relational support requires an understanding of the information that recipients use to judge support as well as how early in an acquaintance meaningful support judgments can be made. In addition, investigators must identify appropriate prediction models as the dominant, trait-based prediction models (Wiggins, 1973) are not well suited for this task. The studies presented here make progress on these basic research questions.

The key premise of RRT and the studies presented here is that there is little in the way of objectively supportive providers and that instead perceived support reflects relationships among specific recipient and providers. In the next few paragraphs, we define relational support and briefly review evidence that perceived support is primarily relational.

When recipients each rate the same providers, generalizability (G) theory (Cronbach, Gleser, Nanda, & Rajaratnam, 1972) and the social relations model (SRM; Kenny, 1994; Kenny, Kashy, & Cook, 2006) each can estimate the extent to which providers' supportiveness reflects relationships among recipients and providers, the objective supportiveness of providers, and the trait-like tendencies of recipients to see all providers as more or less supportive (Lakey, 2010; Lakey et al., 1996). Definitions of these and other important concepts are provided in the Appendix.

When recipients rate the same providers on supportiveness, relational support reflects systematic disagreement among recipients about the relative supportiveness of providers. For example, Recipient A might view Provider A as more supportive than Provider B, whereas Recipient B might view Provider B as the more supportive. Phrased differently, relational support reflects the extent to which support is a matter of personal taste. Relational support is mathematically identical to Person $\times$ Situation interactions as defined by Endler and Hunt (1969) and to "if . . . then, situation–behavior relations" as defined by Shoda, Mischel, and Wright (1994, p. 684) as well as by Mischel and Shoda (1995). Following Shoda and colleagues, it is useful to think of relational support in terms of profiles. Relational support reflects the extent to which each recipient has an idiosyncratic profile that describes her or his perceptions of the supportiveness of a set of providers. Relational support will be large insofar as recipients have different profiles and will be small insofar as recipients have similar profiles.

Provider influences reflect differences among providers in their supportiveness, averaged across recipients. For example, recipients might view Provider A as more supportive than Provider B. Provider influences and interrater agreement are identical statistically and thus provider influences reflect the objective supportiveness of providers, insofar as interrater agreement indexes objective features.

Recipient influences reflect average differences among recipients in their ratings of the same providers. For example, Recipient A might view all providers as more supportive than does Recipient B.

Research has consistently found that perceived support is primarily relational, followed in size by recipient influences. Provider influences have been surprisingly small. As summarized by Lakey (2010), the most convincing studies are those in which recipients all rated providers who were well known to recipients. For example, in Lakey and colleagues' (1996) Study 1, graduate students in a PhD program rated program faculty. In Study 2, sorority members rated randomly selected sisters. In Giblin and Lakey (2010), medical fellows rated program faculty. In Branje, van Aken, and van Lieshout (2002) and Lanz, Tagliabue, and Rosnati (2004), nuclear family members rated each other in round-robin designs. Each of these studies found that the strongest influences on perceived support were relational. Sample-weighted, mean proportions of variance explained were .62 for relational influences, .27 for recipient influences, and .07 for provider influences (Lakey, 2010). Thus, there appears to be relatively little in the way of objectively supportive providers that most recipients perceive as supportive. Thus, although an investigator might hire a support provider because the provider strikes the investigator as supportive, it is unlikely that the investigator's perception will generalize to other recipients.

As described previously, RRT recommends interventions that harness the large magnitude of relational support by matching recipients with specific providers so that unusually supportive relationships emerge. Such an approach requires forecasting relational support, which involves predicting each recipient's unique profile across different providers. For example, one needs to forecast that Recipient A will find Provider A highly supportive, Provider B moderately supportive, and Provider C unsupportive, but that Recipient B will display the opposite profile. Trait-based approaches to prediction are not well suited to forecasting criterion measures that are expressed as profiles (Wiggins, 1973).

Cronbach and colleagues' (1972) multivariate G analyses (Brennan, 2001a; Strube, 2000) are well suited to forecast profiles across providers, as multivariate G analyses can estimate correlations among constructs specifically for relational influences (as well as for recipient and provider influences). For example, multivariate G analyses have been used to estimate correlations between relational influences on perceived support and relational influences on affect (Neely et al., 2006), perceived similarity (Lakey, Lutz, & Scoboria, 2004; Neely et al., 2006), and the therapeutic alliance (Lakey, Cohen, & Neely, 2008). Forecasting relational support is essentially similar, except that one is predicting relational influences on supportiveness at Time 2 (the criterion) from relational influences on predictor variables at Time 1 (e.g., positive affect). Figure 1 depicts successful and unsuccessful forecasting of relational support. In the top portion of the figure, the predictor profile corresponds well to the criterion profile. Such correspondences would be reflected in strong multivariate G correlations. In the bottom portion, there is a weak correspondence between predictor and criterion profiles, reflected in weak multivariate G correlations.

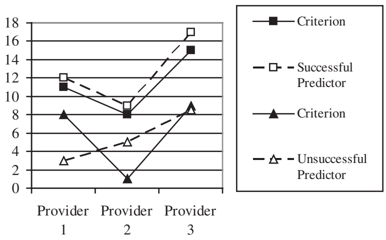


**Figure 1.** Profiles depicting successful forecasting of criterion relational support from a predictor (top portion of figure) and unsuccessful forecasting of criterion relational support from a predictor (bottom portion of figure).

In forecasting relational support, it would be useful to know what information recipients use to judge providers' supportiveness, as well as how early in the acquaintance process meaningful support judgments can be made. Identifying the information used to judge support might enable more accurate forecasts by guiding investigators to gather the most relevant information. If meaningful support judgments can be made very early in an acquaintance, then it should be possible to forecast relational support by providing recipients with very brief exposure to providers. S&CSST and RTT make different predictions regarding these questions.

S&CSST predicts that support judgments are based on enacted support that occurs during conversations about stress. Yet, the magnitude of the link between perceived and enacted support is only modest (Barrera, 1986; Haber, Cohen, Lucas, & Baltes, 2007), and enacted support has not been able to explain perceived support's link to mental health (Lakey, Orehek, Hain, & VanVleet, 2010). Although S&CSST is not explicit on how early in an acquaintance meaningful support judgments can be made, the theory's emphasis on enacted support would seem to imply that meaningful support judgments cannot be made until there were substantial conversations about stress.

RRT predicts that perceived support is inferred in part from favorable affect experienced during ordinary, day-to-day conversations. Conversations about stress and coping are not required although they can contribute to support perceptions. Thus, meaningful support judgments can be made very early in an acquaintance, as soon as a recipient can discern that a conversation elicits favorable affect. According to RRT, recipients and providers regulate affect best when they have similar affective reactions to the content of conversation. Thus, recipients should base support judgments in part on providers' perceived similarity to recipients. In fact, recipients' judgments of providers' similarity to recipients are among the strongest correlates of perceived support (Lakey, Ross, Butler, & Bentley, 1996; Lakey et al., 2004; Neely et al., 2006; Westmaas & Cohen Silver, 2006), although research has not yet investigated whether similarity information can forecast future perceived support. Thus, according to RRT, it should be possible to forecast relational support from each recipient's affect in response to each provider as well as each recipient's judgments of each provider's similarity to the recipient. Further, such forecasting should be possible when recipients have only very brief conversations with providers. RRT predicts that perceived support is inferred almost immediately from positive affect and perceived similarity, and thus recipients' judgments of providers' support from very brief conversations should also forecast criterion support.

### *Overview of the current studies*

To study forecasting relational support, the same providers and recipients must have multiple conversations over time. Thus, in Study 1, each recipient had three conversations with each provider over a 3-week period, and in Study 2, each recipient had five conversations with each provider, typically over a 4-month period. RRT predicts that recipients should be able to make meaningful support judgments from very little information about providers, and thus we expected that we could forecast relational support from recipients' reactions to a single, brief (10- or 20-min) conversation.[1] RRT predicts that recipients base support judgments on their affective reaction to providers as well as their judgments of providers' similarity to recipients. Thus, we assessed recipients' affect in both studies and perceived similarity in Study 2. If one can forecast relational support from single live conversations, perhaps one can also forecast relational support from brief video interviews with providers. In interventions, it would be more efficient if providers could be assigned on the basis of recipients' reactions to videos of providers, rather than on the basis of face-to-face conversations. Study 1 investigated the extent to which video interviews of providers were useful in forecasting relational support.

Yet, recipients' initial reactions to providers might not be good indicators of recipients' longer term reactions. If recipients' reactions are not useful for forecasting relational support, independent observers might be better. Some research has found that observer ratings have higher predictive validity than do self-ratings (MacDonald & Ross, 1999; Mount, Barrick, & Strauss, 1994; Wilson, Laser, & Stone, 1982). In addition, S&CSST states that support is conveyed in the observable actions of providers. Thus, Study 2 also examined the extent to which independent observers could forecast relational support.

In addition to investigating forecasting relational support, Study 1 also attempted to replicate Neely and colleagues' (2006) observation that perceived support was linked to positive affect, but not to low negative affect, when correlations reflected relational influences specifically and when providers were strangers to recipients initially. This is important, because if relational influences on perceived support and affect were uncorrelated, it would seem unlikely that interventions based on manipulating relational support could be successful.

## Study 1

### *Method*

#### *Participants*

Forty-three participants were recruited from a regional Midwestern state university. Forty

1. Research on brief slices of behavior (Ambady & Rosenthal, 1992) also suggests that recipients might be able to forecast provider supportiveness on the basis of surprisingly little information about providers. Thin slices research differs from the current research in important ways, however. For example, thin slices research typically limits to a few seconds the duration of exposure to targets (Ambady & Rosenthal, 1992), whereas in the current studies exposure to providers ranged from 8 to 60 min. In addition, thin slices research commonly isolate target influences (i.e., provider influences) in that the criterion is the pooled ratings of other observers, whereas in the current studies we isolated relational influences specifically.

served as support recipients and 3 as support providers.

Recipients were 18.5-year-old (mean), first-semester freshman. Eighty-five percent were female, 73% were of European ancestry, and 18% were of African ancestry. Recipients were recruited from fliers posted on campus announcement boards as well as from visits by the authors to introductory psychology classes. Recipients received $10 at the end of each session.

Providers were 23-year-old (mean) female, upper-level psychology majors of European ancestry. Providers were recruited on the basis of their reliability, as recommended by psychology faculty members. Providers received $10 for each session. No recipients or providers were lost to follow-up.

### *Procedure*

At an initial meeting, providers were briefed on the purpose of the study and given the questions to be posed in the video-recorded interview. Two to 3 days later, providers signed consent forms, provided demographic information, and participated in the interviews. The interviewer (Amy Veenstra) asked questions about providers' life goals, hobbies, dislikes, their reasons for attending the university, their experiences in college, and their advice for freshmen in adjusting to college. Each interview lasted about 8.5 min.

Each recipient attended three 3-conversation sessions during which each recipient had 10- (first session) and 20-min (Sessions 2 and 3) one-on-one conversations with each provider. Thus, the study was composed of 360 conversations. Sessions were typically scheduled 1 week apart.

There were three recipients and three providers at each session. At the first session, recipients were provided with consent forms and demographic sheets to complete upon arrival. Recipients next viewed the first video interview. Recipients were asked to pay close attention as they would be answering questionnaires about the interview. After viewing the first interview, recipients completed measures of the expected supportiveness of the provider, as well as affect experienced while viewing the interview. This sequence was repeated with Interviews 2 and 3. Recipients viewed videos in groups of three and were asked by the experimenter (who was present) not to discuss the videos. Providers were in an adjacent room while recipients viewed the interviews and recipients had no contact with providers prior to viewing the interviews. After viewing the interviews, recipients met individually with each provider. To provide some structure for the conversation, recipients were asked to discuss for 10 min the stressors freshmen encounter when adjusting to college. After the first conversation, recipients completed measures of provider supportiveness and affect experienced during the conversation, provided a brief description of the topic discussed, and rated the stressfulness of the conversation topic. Recipients then moved to another room for a conversation with the next provider and completed the same measures. At the second session 1 week later, recipients were reminded to discuss stressors that freshmen encounter in college. Conversations with each provider then followed the same procedure as in Session 1, except that each conversation lasted 20 min. This procedure was repeated for Session 3. Participants were debriefed after the final conversation.

Providers were instructed to allow recipients to lead the conversations. If recipients had difficulty in maintaining a conversation on the topic, providers directed the conversation to stressors at college. Note that recipients were not required to discuss their own experience of college stress and were free to discuss the topic in abstract terms, or with regard to other students. Providers completed two sessions on each of 2 days a week for a total of four sessions a week.

To minimize order effects, this study used a Latin squares design. The room in which recipients had their first conversation was determined by their order of entry into the study. The room in which conversations were held was rotated to the right for each subsequent session, which allowed each recipient to converse with each provider in each sequential position. Providers were assigned a start room for each new group of recipients and were then rotated one room to the left for each new conversation. This allowed each provider to converse with each recipient in each room. Thus, recipients were presented with providers and rooms in a different order for each of the three conversations.

To summarize, at each recipient's first session, he or she first viewed three video interviews with each of the three providers, and rated provider supportiveness and her or his own affect experienced when viewing the interviews. Next, the recipient moved to a room and had a 10-min conversation with one provider, after which the recipient rated affect and provider supportiveness. The recipient moved to the next room and had a conversation with the next provider, after which he or she moved to the third room and conversed with the third provider. The following week, the recipient had conversations with each of the three providers, but in a new order. In the third week, this procedure was repeated with a new order.

### Measures

*Provider supportiveness.* Recipients rated providers using seven items from the Social Provisions Scale (Cutrona & Russell, 1987) as modified by Neely and colleagues (2006) for assessing provider supportiveness after brief conversations. The Social Provisions Scale is a widely used measure with established reliability and validity (Wills & Shinar, 2000). When recipients rated the video interviews, the scale asked recipients to estimate the likely supportiveness of each provider. Internal consistency reliabilities were .72 for recipient influences and .86 for relational influences.[2]

*Affect.* The Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988) was used to measure affect. The PANAS is a 20-item scale reflecting two mostly distinct factors: positive and negative affect. The PANAS has established reliability and validity, and the scale's state form is sensitive to momentary changes in affect and was therefore appropriate for the goals of the study. Participants were asked to "indicate to what extent you felt this emotion during the time that you interacted with the person you just talked with." Internal consistency reliabilities were .96 and .87 for recipient influences on positive affect and negative affect, respectively, and .98 and .00 for relational influences for positive affect and negative affect, respectively. The zero value indicates that there was no relational variance for negative affect, as described momentarily in the results.

*Stressfulness of conversation topics.* For descriptive purposes, as in Neely and colleagues (2006), participants rated the most stressful topics discussed for each conversation using a 4-point scale, ranging from *not at all stressful* to *very stressful*. Recipients also provided a brief description of the topic rated. Twenty-two percent of participants rated the topic as *not at all stressful*, 41% rated their conversation topics as *a little stressful*, 27% rated their topic as *stressful*, and 11% as *very stressful*. As suggested by the stressfulness ratings, most conversation topics were fairly ordinary, although some were very stressful. The stressful topics included hate crimes, credit load, professors, sexual assault, roommates, and deaths in the family.

### Analytic strategy

Generalizability analysis estimated the proportion of variance explained by recipient, provider, relational and Relational × Conversation influences for provider supportiveness, positive affect, and negative affect. Odd and even items were aggregated to form two composites to decrease measurement error and simplify the design. The items factor was composed of two levels (the average of odd items and the average of even items). Thus, the study was a 40 (recipient) × 3 (provider) × 3 (conversation) × 2 (item) fully crossed design with random factors.

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2. Internal consistency reliability was estimated using these formulas: $\alpha^2{}_{\text{rec}} = \sigma^2{}_{\text{rec}}/(((\sigma^2{}_{\text{rec}} + ((\sigma^2/{}_{\text{rec}\times i})/n_i)))$ and $\alpha_{\text{rel}} = \sigma^2{}_{\text{rel}}/(((\sigma^2{}_{\text{rel}} + ((\sigma^2{}_{\text{rel}\times i})/n_i)))$ for which rec = recipient variance, rel = recipient by provider variance (i.e., relational variance), rec × $i$ = Recipient × Item variance, rel × $i$ = Recipient × Provider × Item variance, and $n_i$ = number of items. We do not report reliability for provider influences as there were no significant provider influences in the current studies.

Recipient, provider, and relational influences have been described previously. Following Neely and colleagues (2006), the inclusion of multiple conversations in the design permit one to distinguish between relational influences that are stable across conversations (Recipient × Provider effects) and relational influences that vary from conversation to conversation (Recipient × Provider × Conversation effects). As an example of relational influences that vary from conversation to conversation, a provider that is unusually supportive to a specific recipient averaged across all occasions (i.e., relational support) might be unusually supportive in one conversation but only moderately supportive in another conversation (a Relational × Conversation effect).

Analyses were conducted using the variance components procedure in SPSS (SPSS, Inc., 2005) using restricted maximum likelihood estimation. G designs typically have only one observation per cell, and thus the highest order interaction is used as the error term (Recipient × Provider × Conversation × Item in this study).

Multivariate G analyses were conducted using Mgenova (Brennan, 2001b). As there are no parametric significance tests for multivariate G correlations, we used the normal approximation bootstrapping method (Mooney & Duval, 1993), following our research team's previous work (e.g., Barry, Lakey, & Orehek, 2007; Lakey et al., 2008, 2010; Lakey & Scoboria, 2005; Neely et al., 2006). Bootstrapping estimates standard errors by taking multiple resamples (with replacement) from study data. The $z$ distribution is used in the normal approximation method to determine conventional probability values. Multivariate G correlations are significant when they exceed 1.96 × the standard error. Although as few as 50 resamples can provide adequate estimates of standard errors (Mooney & Duval, 1993), in the current study we drew 100 resamples using STATA (StataCorp, 2003) to increase precision. Relatively few resamples were a practical necessity when using Mgenova because the program required manual bootstrapping.

### *Results*

Forecasting criterion relational support requires that there are significant relational influences for perceived support and affect. As shown in Table 1, there were significant relational influences for both perceived support and positive affect, but not for negative affect. In addition, there were significant recipient and Relational × Conversation influences for perceived support, positive affect, and negative affect. Provider influences were small and not significant for all constructs.

Our primary goal was to investigate the extent to which we could forecast relational support, that is, to forecast the specific providers that specific recipients would perceive as unusually supportive. The criterion

**Table 1.** *Magnitude of recipient, provider, relational, and Relational × Occasion influences on perceived social support, positive affect, and negative affect from Study 1*

| | Perceived social support | | | Positive affect | | | Negative affect | | |
|---|---|---|---|---|---|---|---|---|---|
| Influence | Var | *SE* | Effect size | Var | *SE* | Effect size | Var | *SE* | Effect size |
| Recipient | .052* | .022 | .167* | .268* | .079 | .373* | .011* | .006 | .119* |
| Provider | .015 | .016 | .048 | .003 | .007 | .005 | .001 | .001 | .007 |
| Relational | .025* | .010 | .080* | .038* | .020 | .053* | .000 | .000 | .000 |
| Relational × Occasion | .046* | .009 | .147* | .194* | .026 | .270* | .021* | .003 | .221* |
| Error | .062 | — | .201 | .064 | — | .089 | .025 | — | .260 |

*Note.* Var = variance estimate; *SE* = standard error of the variance estimate. Effect sizes are proportion of variance explained.
$^{*}p < .05$.

**Table 2.** *Multivariate G correlations forecasting criterion support for relational and recipient influences in Study 1*

| | Relational | | Recipient | |
|---|---|---|---|---|
| | ρ | *SE* | ρ | *SE* |
| Recipients' perceived support in Conversation 1 | .42* | .09 | .82* | .09 |
| Recipients' perceived support in viewing the interview | .04 | .13 | nc | nc |
| Recipients' positive affect in Conversation 1 | .31* | .15 | .31 | .28 |
| Recipients' positive affect in viewing the interview | −.19 | .14 | .35 | .20 |
| Recipients' negative affect in Conversation 1 | −.09 | .15 | nc | nc |
| Recipients' negative affect in viewing the interview | .05 | .09 | .23 | .21 |

*Note. SE* = standard error; nc = not calculated because one or both the variables had no significance variance in univariate analyses.
*$p < .05$.

was relational support averaged across the final two conversations. Predictors were relational perceived support and recipients' affect assessed after the video interview, as well as after recipients' first 10-min conversations with providers. As shown in Table 2, both recipients' perceptions of support and their positive affect from the first 10-min conversation significantly forecasted criterion relational support. That is, when a provider elicited unusually high or low perceived support or positive affect in a recipient after a 10-min conversation, that provider continued to elicit unusually high or low perceived support in later conversations. Criterion relational support could not be forecasted from recipients' reactions to the video interviews or from recipients' negative affect.

Although not the primary goal of the study, we also examined the extent to which the recipient trait component of perceived support could be forecasted (Table 2). When correlations reflected recipient influences, recipients' support perceptions in the first conversation forecasted with impressive accuracy support perceptions in the last two conversations. That is, after the first round of 10-min conversations, recipients that saw all providers as more supportive than did other recipients, and continued to see all providers as more supportive in subsequent conversations. In contrast, recipient influences on supportiveness in the video interview did not forecast support perceptions in the last two conversations, and recipient influences on positive and negative affect did not forecast recipient influences on supportiveness.

An additional goal of Study 1 was to replicate Neely and colleagues' (2006) findings that provider supportiveness and recipient affect were linked when correlations reflected relational influences. As shown in Table 3, provider supportiveness and recipient positive affect (but not negative affect)

**Table 3.** *Multivariate G correlations (and SEs) among perceived support, positive affect, and negative affect from Study 1*

| | Perceived support | Positive affect | Negative affect |
|---|---|---|---|
| Perceived support | | | |
| Recipient | | .50* (.20) | −.30 (.26) |
| Provider | | nc | nc |
| Relational | | .77* (.33) | nc |
| Relational × Occasion | | .31* (.09) | .04 (.11) |
| Positive affect | | | |
| Recipient | | | .06 (.24) |
| Provider | | | nc |
| Relational | | | nc |
| Relational × Occasion | | | .17 ( 11) |

*Note.* nc = not calculated because one or both the variables had no significance variance in univariate analyses.
*$p < .05$.

were significantly linked when correlations reflected relational influences that were stable across conversations as well as relational influences that varied across conversations (i.e., Relational $\times$ Occasion influences). That is, providers that elicited unusually high or low perceived support in recipients also elicited unusually high or low positive affect. In addition, provider supportiveness and recipient positive affect (but not negative affect) were significantly linked when correlations reflected recipient influences. That is, recipients that characteristically perceived providers as supportive across conversations also characteristically experienced positive affect. As there were no significant provider influences, it was not meaningful to estimate multivariate G correlations for those influences.

### *Discussion*

RRT (Lakey & Orehek, 2010) predicts that social support interventions will be more effective if they harnessed the very strong relational influences on perceived support and matched providers with recipients such that unusually supportive relationships emerged. Yet, for such interventions to move forward, progress must be made on a number of basic research questions. Most important, it must be possible to forecast relational support. Research needs to identify the information that recipients use to make support judgments, how early in the acquaintance process meaningful support judgments can be made, and the appropriate prediction models. Study 1 contributes to addressing each of these basic research questions.

According to RRT, recipients judge provider supportiveness, in part, from the extent to which providers elicit favorable affect in recipients during ordinary conversations, and recipients can make meaningful support judgments with very little exposure to providers. In Study 1, we could forecast relational support from recipients' affective reactions to and perceived supportiveness of providers in response to single, 10-min conversations. For example, if after one conversation Corey found Lena to be supportive and she elicited positive affect in him, then he continued to find her supportive in subsequent conversations. Thus, Lena would likely be a good match for Corey, beyond whether she is perceived to be supportive by other recipients and beyond Corey's general tendency to see providers as supportive.

Apparently, providers could elicit sufficient affect in recipients within 10 min for recipients to make meaningful support judgments. According to RRT, discussions of stress and coping is not required for making support judgments, and intimate discussions of stress and coping typically do not occur very early in acquaintance. In Study 1, intimate discussions of stress and coping likely did not commonly occur within the first 10 min, but as predicted by RRT, this did not prevent recipients from making meaningful support judgments.

Study 1 also demonstrated appropriate methods for studying forecasting relational support. Relational influences must be separated from provider and recipient influences, and this requires that recipients interact with the same providers. Of course, to study forecasting, there must be multiple conversations over time. Another key is the use of appropriate statistical tools that can estimate correlations among constructs when both the predictor and criterion variables are expressed as profiles. We used multivariate G analyses in Study 1 (Cronbach et al., 1972), but the SRM (Kenny, 1994; Kenny et al., 2006) would also be appropriate.

In addition to estimating correlations among constructs that reflect relational influences specifically, multivariate G analyses can also estimate correlations among constructs for other influences. This is important because constructs can have different patterns of correlations when different influences are analyzed (Lakey, 2010; Lakey et al., 2010). For example, criterion support could be forecasted with greater accuracy when support reflected recipient influences than when support reflected relational influences. For example, we could forecast Corey's tendency to see all providers as supportive in subsequent conversations from our observation that Corey saw all providers as supportive in the first conversations. Forecasting recipient influences on support makes use of trait-based prediction because each recipient has a single score for each predictor and criterion measure. This is in contrast to forecasting relational support for which each recipient has a profile of scores for each predictor and criterion measure.

Unexpectedly, we could not forecast relational support from recipients' reactions to video interviews of providers. Given that it would be much more efficient in support interventions to forecast relational support from video interviews than from face-to-face interactions, future research should determine how video interviews can be modified to effectively forecast relational support. Perhaps video interviews would permit better prediction if they were longer, provided more information, depicted providers offering enacted support, or depicted providers talking with a wider range of interviewers. It might be especially important to depict providers talking with a wider range of interviewers because when interviewed by only one person (as in Study 1), much of providers' actions might be unique to that specific interviewer. Forecasting relational support focuses on how each provider will be unusually supportive to each recipient, yet the interview might have conveyed primarily how each provider responded uniquely to the interviewer. Of course, it is also possible that there is no substitute for face-to-face conversations in forecasting relational support.

Study 1 also confirmed Neely and colleagues' (2006) very strong link between perceived social support and positive affect when correlations reflected relational influences. The estimates of this link in the two studies were remarkably similar ($\rho = .77$ in the current study and $\rho = .78$ in Neely et al., 2006). When a given provider elicited unusually high perceived support in a given recipient, consistently across conversations, that provider also elicited unusually high positive affect in that recipient. For example, Lena elicits more favorable positive affect in and more perceived support from Corey than Lena typically elicits in other recipients and more than Corey typically experiences with other providers. This link is important because it suggests that an intervention that produced increases in relational support might also produce increases in positive affect. In addition, both Study 1 and Neely and colleagues (2006) found significant links between support and positive affect when correlations reflected relational influences that varied across conversations. That is, on a conversation-by-conversation basis, when a provider elicited unusually high positive affect in a recipient, the recipient saw that provider as unusually supportive. For example, although Lena elicits unusually high positive affect and perceived support in Corey, this varies from conversation to conversation. Some conversations are unusually good, but others, not so much.

Consistent with Neely and colleagues (2006), perceived support was not linked to low negative affect when correlations reflected relational influences. The absence of such a link conflicts with eight studies in which recipients rated their most important support providers (Barry et al., 2007; Lakey et al., 2010; Lakey & Scoboria, 2005). In both Study 1 and in Neely and colleagues, providers were strangers to recipients when the study began, and perhaps the link between perceived support and low negative affect is absent in relationships of short duration. Perhaps the relational link between low perceived support and negative affect emerges when providers criticize recipients or when disagreements lead to heated arguments. Perhaps it takes more than a handful of conversations for such interactions to emerge.

Study 1 found a significant link between support and positive affect when correlations reflected recipient influences. That is, the recipients that characteristically experienced positive affect across providers and conversations also characteristically perceived providers as supportive. For example, Corey might experience positive affect with all providers and see them all as supportive, regardless of their personal characteristics. This effect has been consistently observed by our research team (Barry et al., 2007; Lakey et al., 2010; Lakey & Scoboria, 2005; Neely et al., 2006). Like Neely and colleagues

(2006), Study 1 did not observe a link between perceived support and low negative affect when correlations reflected recipient influences. These findings conflict with the results of studies in which recipients rated their most important support providers (Barry et al., 2007; Lakey et al., 2010; Lakey & Scoboria, 2005).

Finally, we found very small and non-significant provider influences for supportiveness that accounted for only about 5% of the variance. Though small, this estimate is nearly identical to the meta-analytic estimate of 7% (Lakey, 2010). We should note, however, that Study 1's sample of only three providers did not provide the statistical power to detect such small provider influences. In the General Discussion, we generate hypotheses from RRT about why provider influences appear to be so low.

## Study 2

The goals of Study 2 were to replicate Study 1's findings that we could forecast relational support from recipients' positive affect and perceived support from single conversations. In addition, Study 2 tested additional hypotheses. First, Study 2 tested RRT's hypothesis that we could forecast relational support from recipients' judgments of providers' similarity to recipients. Study 2 also provided a better test of RRT's hypothesis that meaningful support judgments can be made regardless of whether recipients and providers discussed stress and coping. In the first two conversations of Study 2, recipients and providers were not prompted to discuss stressors. Study 2 also lengthened the period of time between the initial conversations and the criterion conversations. In Study 1, the initial conversations and the first criterion conversations were separated by 1 week. In Study 2, the typical span between the first predictor and the criterion conversations was 4 months. Study 2 also examined the extent to which additional conversations could increase the accuracy by which relational support could be forecasted. Finally, we examined the extent to we could forecast relational support from independent observers' ratings of video recordings of the conversations.

### *Method*

Study 2 analyzed data gathered by Neely and colleagues (2006), but none of the analyses reported here were reported by Neely and colleagues. More detailed descriptions of the sample and procedures are provided in the original report.

#### *Participants*

Fourteen participants were recruited through flyers posted on a large Midwestern urban university. Ten of the participants were support recipients, whereas 4 served as support providers. The providers ranged in age from 20 to 25 years ($M = 23$). Recipients ranged in age from 19 to 49 years ($M = 30$). Participants were from a variety of ethnic backgrounds with the majority of participants working on undergraduate degrees in a wide range of fields. Participants received $5 following each session. One of the original 11 recipients was lost to follow-up.

#### *Procedure*

Informed consent was obtained from all recipients and providers. Recipients met with providers on five separate occasions for 20 min for a total of 200 conversations. Recipients were invited to discuss any topic, except for Conversation 3 for which recipients were asked to discuss a stressful event. All interactions were videotaped through a one-way mirror. Microphones were discreetly placed in the room to record audio. Following each interaction, recipients and providers were separated, and recipients completed the same measures of perceived support, affect, and conversation topic stressfulness as in Study 1, with the addition of a scale assessing the perceived similarity of providers to recipients developed by Lakey and colleagues (1996). Internal consistency reliabilities of the measures were .77, .92, .86, and .96 for recipient influences on support, positive affect, negative affect, and similarity, respectively. Reliabilities were .97, 1.00, 1.00, and .95 for relational influences on support, positive affect, negative affect, and similarity, respectively. The 1.00 values indicated that Relational $\times$ Item interaction variance was zero. The median duration of time between adjacent conversations (i.e., Conversations 1 & 2, 2 & 3, etc.) with the same providers was 37 days (range = 16–86 days). The median duration between the first predictor conversation (i.e., Conversation 1) and the first criterion conversation (i.e., Conversation 4) was 122 days (range = 104–148 days). Variation in duration between conversations reflected scheduling difficulties.

Ratings of topic stressfulness were similar to those in Study 1. Thirty-four percent were rated as *not at all stressful*, 48% were rated as *as a little stressful*, 14% were rated as *stressful*, and 6% were rated as *very stressful*. As suggested by the stressfulness ratings, most conversation topics were fairly ordinary, although some were very stressful. The stressful topics included father's colon cancer, gambling debts, eviction from apartment, and romantic breakups.

*Observer ratings.* For each of the 200 videotaped interactions, six independent observers rated recipients' affect and providers' supportiveness, using the same measures as recipients, with instructions modified to reflect the role of observers. For recipient influences, interrater reliabilities were .90 for provider supportiveness, .95 for recipient positive affect, and .92 for recipient negative affect. For relational influences, interrater reliabilities were .80 for provider supportiveness, 1.00 for recipient positive affect, and .86 for recipient negative affect.

### Results and discussion

As reported by Neely and colleagues (2006), there were significant recipient, relational and Relational × Conversation influences on perceived support and positive affect. There were significant recipient and Relational × Conversation influences on negative affect. There were no significant provider influences.

Replicating Study 1, we could forecast relational support from recipients' perceptions of providers' supportiveness and recipients' positive affect from a single, face-to-face conversation (Table 4). In addition, recipients' perceptions of providers' similarity to recipients forecasted relational support. It is remarkable that a single, 20-min conversation could forecast relational support 4 months later. Yet, consistent with Study 1, relational support could not be forecasted from recipients' reports of negative affect.

Study 2 also examined the extent to which we could forecast relational support more accurately when recipients had additional conversations with providers. Thus, we compared predictive accuracy when the predictor was based on the first conversation, the average of the first two as well as the average of the first three conversations. Following Lakey and colleagues (2010), we tested the significance of the differences in correlations by estimating the standard errors of the differences, using normal approximation bootstrapping. As seen in Table 4, similar to Study 1, relational support could not be forecasted from recipients' negative affect even after two or three conversations. There were modest and nonsignificant increases in predictive accuracy for perceived support, positive affect, and perceived similarity as recipients had more conversations with providers (standard errors of the differences ranged from .034 to .118). Of course, it might have been possible to detect these trends with greater statistical power. The multivariate G correlations in Study 2 were based on 40 observations (10 recipients × 4 providers). Thus, future research with greater statistical power should revisit whether additional conversations beyond one can enhance the accuracy of forecasting relational support as well as whether additional conversations are cost effective within the context of interventions. Nonetheless, Study 2's results suggest that forecasting relational support might be sufficiently accurate when based on a single conversation and that additional conversations might add relatively little to predictive accuracy.

Although some research has indicated that independent observers sometimes add incremental validity to participants' predictions (MacDonald & Ross, 1999; Wilson et al., 1982), this was not detected in this study. Observers were not able to forecast relational support on the basis of observing provider supportiveness or from observing recipients' expression of affect (Table 4). We wondered

**Table 4.** *Multivariate G correlations forecasting criterion support for relational support and recipient influences in Study 2*

| | Relational support | | | | | | Recipient influences | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Forecasting relational support from first conversation | | Forecasting relational support from first two conversations | | Forecasting relational support from first three conversations | | Forecasting recipient support from first conversation | | Forecasting recipient support from first two conversations | | Forecasting recipient support from first three conversations | |
| | ρ | *SE* | ρ | *SE* | ρ | *SE* | ρ | *SE* | ρ | *SE* | ρ | *SE* |
| Recipients' perceptions of providers' support | .43* | .15 | .45* | .17 | .53* | .17 | .81* | .25 | 1.02* | .17 | 1.04* | .13 |
| Recipients' positive affect | .48* | .16 | .47* | .15 | .60* | .10 | .65* | .27 | .70* | .22 | .63* | .23 |
| Recipients' negative affect | −.03 | .20 | −.00 | .12 | −.07 | .18 | .72 | .89 | −0.15 | .62 | −0.15 | .49 |
| Recipients' perceptions of providers' similarity | .44* | .18 | .42* | .19 | .48* | .19 | 1.01* | .29 | 1.04* | .21 | 1.01* | .14 |
| Observers' reports of recipients' positive affect | .34 | .21 | .04 | .22 | .12 | .25 | .10 | .52 | .05 | .52 | .03 | .53 |
| Observers' reports of recipients' negative affect | .07 | .14 | .08 | .17 | .18 | .17 | −.30 | .80 | −.47 | .66 | −.20 | .56 |
| Observers' report of provider supportiveness | .06 | .20 | −.02 | .16 | −.04 | .16 | −0.14 | .59 | −.18 | .79 | −.11 | .72 |

*Note*. Some correlations exceed 1 because multivariate G correlations are population estimates.
$^{*}p < .05$.

if observers could not forecast relational support because they could not detect recipients' subjective experience of affect during conversations. As described previously, in both Studies 1 and 2, we could forecast relational support from recipients' subjective experiences of positive affect during the first conversation. Yet, observers could not detect recipients' positive affect in Study 2 data, as there was no agreement between observers' ratings of recipients' positive affect and recipients' reports of their own positive affect, when correlations reflected relational influences (Neely et al., 2006). Thus, observers appeared to lack the primary cues that RRT predicts are used to judge relational support. The inability of observer ratings to forecast relational support does not appear to reflect merely the invalidity of observer ratings, as observer ratings were highly reliable and yielded meaningful links between affect and support for recipient, and Relational × Conversation influences in Neely and colleagues (2006).

Finally, as in Study 1, we could forecast criterion support with very high accuracy when recipient influences were analyzed (Table 4). This finding provides an additional demonstration that correlations between the same constructs can differ when estimated separately for recipient and relational influences.

## General Discussion

RRT (Lakey & Orehek, 2010) provides new approaches to social support interventions whereby novel providers are matched to recipients such that unusually supportive relationships emerge. This approach is suggested by research indicating that relational influences are the strongest determinants of perceived support yet identified, when established relationships are studied. New approaches to social support interventions are important because randomized controlled trials of existing interventions have been disappointing. Yet, before interventions based on relational principles can be implemented, progress must be made on a number of basic research questions. These include: Can relational support be forecasted? What information do recipients use to judge support and can this information be used to forecast relational support? How early in an acquaintance can meaningful support judgments be made? What are appropriate prediction models for forecasting relational support?

The most important finding from the current studies was that we could forecast which recipient and provider dyads would develop unusually supportive relationships, indicating that it should be possible to match specific providers with recipients to maximize perceived support. Predictive accuracy was fairly strong, comparable to the accuracy by which conscientiousness forecasts job performance (Ones, Viswesvaran, & Schmidt, 1993) and smoking forecasts lung cancer (Bushman & Anderson, 2001).

RRT predicts that recipients judge support from the affect experienced during conversations with providers, as well as from the perceived similarity of providers to recipients, and that recipients can make meaningful support judgments very early in an acquaintance, regardless of whether stress and coping are discussed or enacted support is provided. The studies presented here were mostly consistent with hypotheses. Recipients' positive affect and perceived provider similarity were both effective forecasters of subsequent relational support. Recipients could make meaningful support judgments within 10 min of meeting a stranger and in conversations in which recipients were not prompted to talk about stressors.

Some of our current findings were inconsistent with previous research. We suspect that these discrepancies reflect the fact that in the current studies, recipients and providers were strangers initially. For example, negative affect was not linked to low perceived support for relational influences. Yet, in dyads of many years' duration, negative affect has been consistently linked to low perceived support (e.g., Barry et al., 2007; Lakey et al., 2010; Lakey & Scoboria, 2005). We suspect that negative affect and low perceived support emerge when recipients and providers argue or when providers criticize recipients, and that it takes more than three to five conversations for such interactions to occur. Thus, such effects are captured in studies of long-standing dyads, but not in studies of brief acquaintances. Another difference between the current findings and previous research is that in the current studies, the magnitude of recipient and relational influences were not significantly different. Yet, in studies of providers well known to recipients, relational influences are approximately 3 times larger than recipient influences (Lakey, 2010). We suspect that the difference between the current studies and previous research merely reflects that brief acquaintances have limited ability to influence recipients' perceived support. Relationships likely have an increasingly powerful influence on recipients in dyads of longer duration and as a result, the role of recipient personality, as a percentage of total variance, would be expected to diminish.

That there was little in the way of objectively supportive providers might surprise some readers, but this is a well-replicated effect, and the magnitude observed in the current studies is nearly identical to the meta-analytic estimate (Lakey, 2010). Converging evidence is provided by psychotherapy research that provides nearly identical estimates of the extent to which some therapists (i.e., providers) are more effective than other therapists (Wampold & Brown, 2005). RRT offers a potential explanation for comparatively small provider influences in social support. According to RRT, the main effect between perceived support and favorable affect emerges in social interaction in which recipients and providers engage in shared activities and talk about other people and things. Each recipient and provider has a separate profile of affective reactions to these other people and things. A recipient's affect will be well regulated insofar as the recipient and a given provider have similar profiles. For example, a recipient and provider will be well matched if they both like to talk about their children, TV celebrities, and bake pastry. They will be badly matched if the provider does not cook and finds conversations about children and celebrities dull. Most providers will not match most recipients especially well at this level of detail, and thus a given provider will not be seen as supportive by most recipients, resulting in comparatively small provider influences and comparatively large relational influences.

Future research could investigate ways to improve the accuracy and efficiency of forecasting relational support. The current studies found that only face-to-face conversations were useful in forecasting. Yet, it will be important to develop methods that do not require face-to-face conversations, as such conversations across a large number of recipients and providers would be inefficient. Future research should investigate more extensive and varied video interviews with providers, as well as personality similarity and complementary between recipients and providers (Benjamin, 1974). Attachment theory might be useful in this regard (Collins & Feeney, 2002). For example, people with anxious attachments might prefer a provider who offers very clear and direct support to soothe the individuals' fears of rejection, whereas a person with avoidant attachments might prefer a support provider who is more subtle (cf. Lemay & Clark, 2008).

Although the focus of the current research was on forecasting relational support, the analytic approach could be useful for a wide range of both applied and basic research. For example, the analytic strategy could be used to attempt to improve the effectiveness of teaching and psychotherapy. Gross, Lakey, Edinger, Orehek, and Heffron (2009) found large relational influences on teaching effectiveness, and thus it might be possible to forecast the specific teachers that would be unusually effective with specific students. Similarly, Lakey and colleagues (2008) found strong relational influences in an analog study of the therapeutic alliance, and thus it might be possible to forecast the specific therapists that would be unusually effective with specific clients.

The analytic approach used in the current studies also contributes to basic research on interactional approaches to personality. As described previously, relational influences are statistically identical to Person $\times$ Situation interactions as defined by Endler and Hunt (1969) when recipients are treated as persons and providers are treated as situations. Yet, to our knowledge, Endler and Hunt did not extend their approach to forecasting anxiety in future situations. Shoda, Mischel, and Wright (1994) as well as Mischel and Shoda (1995) demonstrated how interactional approaches could be used to forecast future behavior by presenting evidence that "if . . . then, situation . . . behavior relations" were stable over time. As described previously, such relations are essentially similar to relational influences and to Person × Situation (P × S) interactions (Shoda et al., 1994). Nonetheless, the multivariate G approach used in the current studies has several advantages over the analytic method taken by Shoda and colleagues. First, unlike Shoda and colleagues' method, the multivariate G approach permits forecasting P × S influences simultaneously for all participants. Shoda and colleagues' method requires forecasting P × S influences separately for each participant, and then averaging results across all participants. Second, the multivariate G approach provides estimates of accuracy in forecasting behavior from both trait-based and P × S-based approaches. For example, in the current studies, prediction from trait-based approaches was more accurate than prediction from P × S-based approaches. Shoda and colleagues' method does not yield separate estimates for predictive accuracy for both trait and P × S approaches. Third, because the multivariate G approach defines trait and P × S influences to be orthogonal, it is straightforward to determine the extent to which forecasting P × S influences provides incremental validity beyond forecasting trait influences. In the current studies, prediction achieved by the P × S approach added predictive accuracy beyond what was achieved by the trait approach. Shoda and colleagues' method does not provide information about incremental validity because it does not provide separate estimates for P × S and trait-based prediction.

Before closing, we note some of the limitations of the current studies. First, the sample sizes of recipients and providers were small, which limited statistical power. For example, although there were small increases in predictive accuracy as recipients had more conversations with providers in Study 2, these increments were not significant. A larger sample might have been able to detect these increments. Second, although the studies were designed to mimic social support interventions in which providers were initially strangers to recipients, recipients were not in obvious need for social support or at risk for mental or physical disorder. Thus, the findings of this study might not generalize to at-risk samples most frequently targeted by social support interventions. Nonetheless, the analytic approach used in these studies could be applied to any sample. Third, a portion of relational influences were unstable over time (i.e., Relational × Occasion influences), and of course, their instability would make them impossible to forecast.

In conclusion, RRT (Lakey & Orehek, 2010) predicts that social support interventions will be more effective if they harness strong relational influences. Yet, to exploit relational support in interventions, progress must be made on a few basic research questions. The studies presented here addressed these basic questions. It was possible to forecast the specific dyads that would develop unusually supportive relationships; recipients appeared to make support judgments on the basis of their own positive affect and from the perceived similarity of providers to recipients. Recipients could make meaningful support judgments from very brief contacts with providers in which little (if any) substantial discussions of stress and coping occurred. Moreover, the appropriate prediction models for forecasting relational support were identified and demonstrated. The next steps could be to develop optimally efficient predictors of relational support and to test whether relational support interventions will be effective in treatment and prevention.

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## Appendix

*Glossary of important terms*

*Terms applied to perceived support*

*Relational support (aka relational influences on perceived support).* When recipients rate the same providers on supportiveness, relational support reflects systematic disagreement among recipients about the relative supportiveness of providers. For example, Recipient A might view Provider A as more supportive than Provider B, whereas Recipient B might view Provider B as the more supportive.

*Recipient influences on perceived support (aka recipient support).* Differences among recipients in their ratings of the same providers, averaged across providers. For example, Recipient A might view all providers as more supportive than does Recipient B.

*Provider influences on perceived support.* Differences among providers in their supportiveness, averaged across recipients. For example, recipients might view Provider A as more supportive than Provider B.

*Relational by occasion influences on perceived support.* Recipients systematically disagree about the relative supportiveness of a set of providers and this disagreement varies from occasion to occasion.

*Criterion relational support.* Relational support that serves as the dependent variable in analyses of forecasting relational support. In both of the current studies, the dependent variable is based on the average of the last two conversations.

*Terms applied to positive affect (terms applied to negative affect are essentially similar)*

*Relational influences on positive affect.* Specific providers elicit unusually high (or low) positive affect in specific recipients, beyond the specific providers' tendencies to elicit positive affect in recipients generally, and beyond specific recipients' tendencies to experience positive affect across all providers. For example, Recipient A might experience more positive affect with Provider A than with Provider B, whereas Recipient B might display the opposite pattern.

*Recipient influences on positive affect.* Differences among recipients in their ratings of their own positive affect in response to the same providers, averaged across providers. For example, Recipient A might experience more positive affect with all providers than does Recipient B.

*Relational by occasion positive affect (aka relational by occasion influences on positive affect).* Specific providers elicit unusually high (or low) positive affect in specific recipients, beyond the specific providers' tendencies to elicit positive affect in recipients generally, and beyond specific recipients' tendencies to experience positive affect across all providers, and these differences change from occasion to occasion. For example, Recipient A might experience more positive affect with Provider A than with Provider B, whereas Recipient B displays the opposite pattern, and these differences change from occasion to occasion.