

Dyadic Models for the Study of Health

Rebecca G. Reed^{1*}, Emily A. Butler¹, and David A. Kenny²

¹ University of Arizona

² University of Connecticut

Abstract

Dyadic designs have been used in health research to investigate intra- and inter-personal mechanisms of health and well-being in various types of dyads, including parent–child dyads, siblings, friends, and romantic partners. Although a growing number of researchers are designing studies that capture the interdependent complexities of relationships, many still need more information on how to analyze the data in a way that maximizes its value. Therefore, the purpose of this review paper is twofold: (1) to address some of the ways in which dyadic data analysis is being used in current health research, with an emphasis on research that has employed the Actor-Partner Interdependence Model, and (2) to propose and explain various methodological and substantive considerations that researchers should consider when using dyadic data analysis in their own research.

A growing number of researchers interested in health are using dyadic- and family-level theories and methodologies to examine the influence of social relationships on health (Kiecolt-Glaser & Newton, 2001; Uchino, 2006; Uchino, Uno, & Holt-Lunstad, 1999), as well the influence of health on social relationships (Belcher et al., 2011; Dorval et al., 2005; Ledyard & Morrison, 2008). Many different others, including romantic partners, friends, siblings, adult children, and health-care practitioners, play an important role in promoting their partner's or patient's health and well-being (Baider, Andritsch, Goldzweig, Uziely, & Ever-Hadani, 2004; Bloom, 1982; Kim, Wellisch, & Spillers, 2008; Manne, Pape, Taylor, & Dougherty, 1999; Northouse, 1988). Furthermore, providing support for a person struggling with illness can take a toll on members of close relationships, including an increased risk of coronary heart disease, elevated neurohormonal and inflammatory responses, and all cause morbidity and mortality due to the stresses of caregiving (Kurtz, Kurtz, Given, & Given, 2004; Lee, Colditz, Berkman, & Kawachi, 2003; Northouse, Williams, Given, & McCorkle, 2012; Rohleder, Marin, Ma, & Miller, 2009; Schulz & Beach, 1999; Vitaliano, Zhang, & Scanlan, 2003). It is clearly important, therefore, to study health and well-being in the context of close relationships and to consider inputs and outcomes for both partners.

Consider, for example, a heterosexual couple, Jane and John, in which Jane has breast cancer and her husband, John, is her support provider. Jane and John are interdependent partners who share certain experiences due to Jane's illness, including adjusting their daily routines, and emotionally relying on each other. However, although they share some similar experiences, Jane's and John's thoughts, emotions, and behaviors may be differentially influenced by her diagnosis. For instance, Jane may feel distressed due to the physical toll of her illness, but John may feel less distressed because he reframes the situation in an attempt to provide the support that Jane needs. Additionally, although Jane faces the challenge of surviving breast cancer, and John's support can play a prominent role in benefitting her well-being, John's health and well-being

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may be affected more or less depending upon his abilities to manage his own stress resulting from her illness.

Fully understanding Jane and John's situation, and developing interventions to optimize their health and quality of life, requires research that considers not just the individual, but also the dyad. A growing number of researchers recognize this and are designing studies that capture the interdependent complexities of relationships, which cannot be fully recognized with individualistic designs. Nevertheless, many still need more information on how to analyze the resulting data in a way that maximizes its value. Ultimately, using dyadic data analyses can provide researchers with new and important insights to interdependent processes that contribute to health outcomes. Therefore, the purpose of this review paper is twofold: (1) to address some of the ways in which dyadic data analysis is being used in current health research, and (2) to propose and explain various methodological and substantive considerations that researchers should consider when using dyadic data analysis in their own research. These goals will be approached by first providing an overview of dyadic data designs and concepts, and second, reviewing and commenting on a selection of health-relevant studies that employed dyadic data analyses.

Overview of Dyadic Designs

There are various dyadic designs including the standard design, one-with-many design, and the social relations model (SRM; Kenny, Kashy, & Cook, 2006). Each of these designs can be cross-sectional or repeated measures over time. In the standard design, each person is linked with one, and only one, other person (meaning each person is a member of one and only one dyad). Generally, the standard design is reciprocal, meaning that both members of the dyad have a score for each variable. An example of a standard design is Jane, the woman with breast cancer presented above, and her husband, John, with the outcome variable being both partners' quality of life scores and the predictor being their coping styles. In this standard dyadic design, Jane would rate her own quality of life and coping style and John would rate his own quality of life and coping style.

The most widely used standard dyadic model is the Actor-Partner Interdependence Model (APIM; Kenny et al., 2006). The APIM simultaneously estimates the effects of one's own characteristics and one's partner's characteristics on an outcome variable. The APIM, therefore, requires two variables, X and Y , where X causes or predicts Y . Importantly, because the APIM assesses both actor and partner effects, both members of the dyad must have scores on both X and Y . As an example, consider the effect of coping with a breast cancer diagnosis on partners' quality of life. It may be that Jane's coping with her breast cancer diagnosis influences both her own and John's quality of life. The effect of Jane's coping with her diagnosis on her own quality of life is called an *actor effect*, and the effect of Jane's coping with her diagnosis on John's quality of life is called a *partner effect* (see Figure 1). Although the APIM is the most widely used model, the standard dyadic design can also be used to study dyad-level or "common fate" effects (Ledermann & Kenny, 2012), or alternatively the model of mutual influence (Kenny, 1996), both of which have been underused in the literature.

Another common dyadic model is the one-with-many design, in which each person is paired with multiple others, but these others are not paired with any other persons. An example of a one-with-many design would be a doctor with many patients (including Jane). In this design, the patients, including Jane, may rate their satisfaction with their doctor so that there are multiple patients each rating the same doctor. Importantly, in the one-with-many design, the patients are not linked to each other; meaning, Jane does not

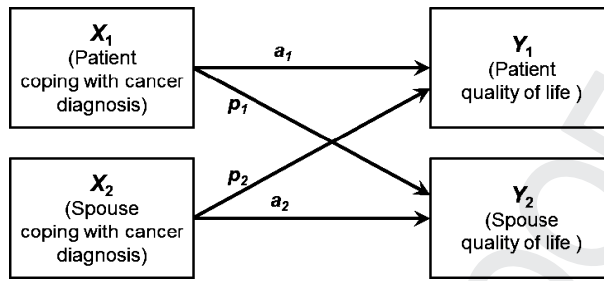


Figure 1 The Actor-Partner Interdependence Model (APIM). An actor effect, denoted as “ a ”, occurs when a person’s score on the predictor variable (X_1) predicts that same person’s score on the outcome variable (Y_1). A partner effect, denoted as “ p ”, occurs when a person’s score on a predictor variable (X_1) predicts her partner’s score on an outcome variable (Y_2). Both members of the dyad have an actor effect and a partner effect.

interact with the other patients. An example of the one-with-many design in the health literature is a study investigating physician-patient agreement, which showed that overall, doctors and their patients had a very different perspective of the doctors’ communication skills that occurred during routine clinical encounters (Kenny et al., 2010).

The last set of designs that we discuss is SRM designs. The prototypical SRM design is a round-robin design in which a group of persons rate or interact with each other, meaning, all persons are linked to everyone in the group. The other major SRM design is the block design in which a group of persons is divided into two subgroups, and members of each subgroup rate or interact with members of the other subgroup. An example of an SRM design is a patient with breast cancer, such as Jane, interacting with a support group of others who also have breast cancer. In this design, each member of the support group rates Jane and all other members, and Jane rates all members of her support group. SRM designs have been used to study persons treated in groups (Mahaffey & Marcus, 2006) and treatment teams (Bagozzi, Ascione, & Mannebach, 2005).

Most Commonly Used Dyadic Designs in Health Research

Dyadic designs have been used in health research to investigate intra- and inter-personal mechanisms of well-being in various types of dyads, including parent-child dyads, siblings, friends, and romantic partners. In any of these dyads, there can be potentially four different configurations of health statuses, such that each partner within the dyad is either diagnosed (D) with an illness, disease, or ailment, or undiagnosed (U). As such, the four major designs are: (1) *Diagnosed/Undiagnosed (DU)* studies, in which one member is diagnosed and the other member is undiagnosed; (2) *Undiagnosed/Undiagnosed (UU)* studies, as might occur in a prevention study of currently healthy couples; (3) *Diagnosed/Diagnosed (DD)* studies, which include cases in which the diagnosis is couple-level, e.g., infertility; and (4) A blend of *DU*, *DD*, and *UU* couples all within the same study, such that one, both, or neither of the members is diagnosed. Research with all of these designs has almost exclusively used the standard dyadic design, and specifically the APIM, to analyze the resulting dyadic data. As such, these studies – each set within a different context due to the dyads’ combined health status (e.g., *UU* versus *DD*) – can advance knowledge of how individuals affect their own and their partner’s health outcomes.

Many researchers have studied dyads in which one member is diagnosed (D), and the other is undiagnosed (U). Very often in *DU* studies, an outcome is measured on only one member, the prototypical case being when a health outcome is measured on only

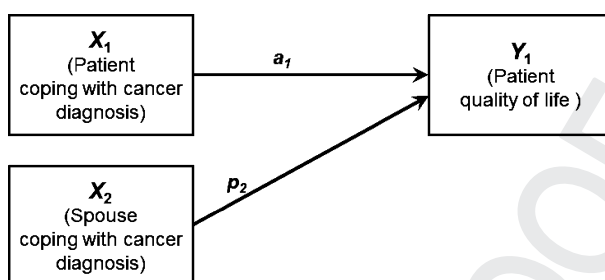


Figure 2 The prototypical example of a DU study in which the health outcome is measured on only the D member (Y_1), but not the U member (hence, Y_2 is missing). The actor (a_1) and partner (p_2) effects can still be measured for the D person (e.g., the patient).

the D member (Y_1). Thus, as depicted in Figure 2, the measurement of the Y_2 variable is missing. Note, however, that actor and partner effects can still be measured for the D person. DU studies are often referred to as “caregiver” or “social support” studies for the evident reason that the undiagnosed member is often providing care or support for the diagnosed member of the dyad. Many of these studies have focused on individuals with diagnoses of a variety of cancers and their undiagnosed family caregivers (Badr, Laurenceau, Scharf, Basen-Engquist, & Turk, 2010; Berg, Wiebe, & Butner, 2011; Dorros, Card, Segrin, & Badger, 2010; Fagundes, Berg, & Wiebe, 2012; Kershaw et al., 2008; Kim et al., 2008; Manne, Badr, & Kashy, 2012; Mellon, Kershaw, Northouse, & Freeman-Gibb, 2007; Porter et al., 2009) and patients undergoing cardiac rehabilitation and their undiagnosed spouses (Hong et al., 2005). As another example, undiagnosed parents and their children with Cystic Fibrosis have also been studied (Driscoll, Schatschneider, McGinnity, & Modi, 2012).

Researchers have also studied dyads in which both members are undiagnosed (UU). These UU studies are often termed “health-promotion” studies because they examine the ways in which members of dyads promote (or hinder) their own and each other’s health and well-being. In these UU studies, neither member of the dyad is diagnosed with a disease, illness, or disorder. Topics of UU studies include the effect of housework on romantic couples’ cortisol levels (Klumb, Hoppmann, & Staats, 2006), partners’ use of social influence tactics to affect each other’s health-related behavior (Butterfield & Lewis, 2002), and the effect of a warm touch intervention on couples’ stress-sensitive physiological systems (Holt-Lunstad, Birmingham, & Light, 2008). Studies of couples with diagnoses and without diagnoses are mutually informative. Therefore, UU studies not only help to inform us about effective ways to promote partner’s health – whether that be by engaging in more housework, or communicating positive social influence tactics – but they also provide us with a template of what “typical” relationship and health-related processes look like. Thus, these UU studies may stimulate and inform effective treatment options for DU or DD couples.

Studies examining dyads in which both members are “diagnosed” (DD) are the least-researched and are an area that warrants future work. Two examples of DD studies include samples of romantic partners undergoing assisted reproduction treatment (Knoll, Schwarzer, Pfüller, & Kienle, 2009; Peterson et al., 2009). These researchers examined the transmission of stress appraisals and depressive symptoms between heterosexual partners and found that transmission occurred, but only in the direction of men transmitting to women (Knoll et al., 2009). In addition, Peterson et al. (2009) found that active avoidance coping was related to higher levels of individual distress in women and men, as well

as increased marital distress in women, over time. The lack of DD studies is likely partially due to researchers arbitrarily designating one partner as the target, or in this case the “diagnosed” partner, even though the other partner may be suffering as well. Therefore, some studies that were conducted as DU studies might have been better framed as DD studies, with measures assessed for both partners. For example, in many mental health studies, it is common to recruit individuals and assess their mental health; however, the partners of these individuals are typically not assessed, despite the fact that they may be clinically distressed as well.

Researchers have also investigated dyads in which one (DU), both (DD), or neither member (UU) has a given diagnosis. Examples of these studies include samples of gay male couples in which one, both, or neither member was HIV positive (Hoff et al., 2009), and samples of heterosexual partners in which one, both, or neither member was diagnosed with Hepatitis C (McMahon, Pouget, & Tortu, 2007). Another example is a study of couples in which one, both, or neither partner was overweight (Markey & Markey, 2011), and couples in which one or both partners continued to smoke, despite one of them having heart or lung disease (Rohrbaugh, Shoham, Butler, Hasler, & Berman, 2009; Shoham, Butler, Rohrbaugh, & Trost, 2007). Lastly, yet another example is a study of mothers with and without Reflex Sympathetic Dystrophy Syndrome (RSDS), and how this diagnosis affected mother’s anger and ultimately their children’s anger (Downey, Purdie, & Schaffer-Neitz, 1999). These studies, in which there is a blend of DU, DD, or UU couples, are the strongest design because they allow comparisons to be made across the different diagnosis-pairings. That is, we can measure three different effects: the D actor effect (e.g., the effect of the disease on the diagnosed actor as compared to the undiagnosed actor), the D partner effect (e.g., the effect of the disease on the diagnosed partner as compared to the undiagnosed partner), and the D actor and partner effect (e.g., some sort of synergistic effect if both members have the disease). If one of three groups is missing (e.g., the DD or UU group), then only two of three effects can be measured.

Key Issues for Dyadic Designs in Health Research

There are a variety of key issues that should be considered when employing dyadic data designs in health research. Addressing these issues can enhance what can be learned from any given study, and can facilitate the accumulation of an integrated body of knowledge, from which effective and efficient comparisons can be made across studies. We focus mostly in this section on DU studies, as they form the bulk of dyadic health studies.

Presence of partner effects

The presence of partner effects is of importance in all of the four designs because they transcend individualistic thinking and elucidate the *interdependent* mechanisms that may influence health. For example, in one study, a partner effect indicated that individuals’ cortisol levels were lower the more time their spouses allocated to housework (Klumb et al., 2006). In another study, a partner effect indicated that the more an individual wanted to change his or her own health-related behavior, the more frequently their partner used social influence tactics that were supportive of that change (Butterfield & Lewis, 2002), suggesting that social relationships are one critical resource for encouraging individuals to be healthier and more active (Gellert, Ziegelmann, Warner, & Schwarzer, 2011). These partner effects are important in that they show the role that partners may

play in promoting each other's health, over and above the effect that individuals have on promoting their own health. Interestingly, for example, in two studies survivors' own age did not predict their fear of cancer recurrence (Mellon et al., 2007) or their uncertainty regarding their cancer (Kershaw et al., 2008), but their partners' age was associated with the survivors' concerns. These partner effects of age have important implications for dyads comprised of younger or older caregivers, and, therefore, warrant further investigation. For example, it may be helpful for diagnosed individuals to discuss how their caregiver's life stage or age impacts their own fears and uncertainties regarding their diagnosis.

Role as a moderator of actor and partner effects

Often in DU research, the key research question is whether actor or partner effects for diagnosed and undiagnosed partners can reveal differences in within-person versus between-person mechanistic-level processes. To test for asymmetry of actor and partner effects by role (i.e., "diagnosed" versus "undiagnosed"), one conducts a series of tests of interactions between the distinguishing feature (e.g., the role, such as "diagnosed" versus "undiagnosed") and the predictor variables (e.g., coping). One observes if any of the interactions by role significantly predicts the outcome variable (e.g., quality of life). If the interaction for the actor variable is significant, then the effect of the diagnosed partner's coping on her own quality of life is different than the effect of the undiagnosed partner's coping on his own quality of life. Similarly, if the interaction for the partner variable is significant, then the effect of the diagnosed partner's coping on her undiagnosed partner's quality of life is different than the effect of the undiagnosed partner's coping on his diagnosed partner's quality of life. For assistance in interpreting interaction effects, see Preacher's online computational tool (Preacher, Curran, & Bauer, 2006).

Identifying asymmetric actor and/or partner effects by testing interactions with role provides important information that could, potentially, focus intervention efforts for both diagnosed and undiagnosed partners (or men and women, or any other distinguishing variable) to reflect either a within-person or between-person emphasis when dealing with various health and relationship issues. One issue to bear in mind is that, if actor or partner effects do vary by role (diagnosed versus undiagnosed), then the intercept difference in the outcome variable will vary depending on how the predictor variable is centered, if at all. We return later to the discussion of intercept differences in the outcome variable between different members of the dyad.

Asymmetries in actor effects are particularly relevant to DU studies because the experience of being ill for the diagnosed individual, and the experience of caring for a diagnosed partner, may be notably different. Therefore, role (diagnosed versus undiagnosed) would likely moderate these actor effects. In Kim et al. (2008), there were differences in actor effects between mothers with breast cancer and their adult caregiving daughters such that both mother's and daughter's psychological distress predicted their own *mental* health, but only mother's psychological distress predicted her own *physical* health. Thus, despite both mothers and their caregiving daughters reporting similar levels of psychological distress, the within-person processes connecting psychological distress and physical health appeared to differ between them. The reason for these differences may be somewhat circular in nature, such that mothers may be more acutely aware of their physical health ailments, making them more psychologically distressed, which in turn, negatively influences their physical health. Because daughters may not be as in tune with their own physical health symptoms (they are comparatively "healthy"), the within-person process linking psychological distress and physical health for daughters may not be relevant. Test-

ing this theory, however, would involve a consideration of time and the investigation of reciprocal associations between psychological and physical health. We return to this issue in a later section.

Another example of asymmetry in actor effects is observed in Mellon et al.'s DU study (2007), in which they examined fear of cancer recurrence in survivors and their caregivers; Individuals (both survivors and caregivers) who reported less positive meaning of the illness had more fear of recurrence, but this relation was stronger for survivors than for caregivers. These findings depict the importance of testing for asymmetry in actor effects by testing interactions with role because certain factors may be more or less salient to diagnosed and undiagnosed individuals, and therefore more or less related to their well-being. For example, because survivors experienced a stronger negative relationship between positive meaning of the illness and fear of recurrence, it could be productive to enlist the help of the *undiagnosed* partners in improving the *diagnosed* partners' meaning of the illness, rather than directly targeting the diagnosed partners' fear of recurrence. Future research is warranted to gain more knowledge regarding which factors are more salient to which types of individuals (D versus U), and what approaches may be most effective for which types of individuals.

Bidirectional influence

Within dyadic studies it is important to examine *bidirectional* influence. Bidirectionality is not established by testing a single hypothesis, but rather two hypotheses. Therefore, bidirectionality is supported only if both partner effects are present (e.g., if X_1 predicts Y_2 and X_2 predicts Y_1 , or in other words the diagnosed partner's X predicts the undiagnosed partner's Y and *vice versa*) (Cook & Kenny, 2005). In addition, bidirectional effects can be either symmetric (the two effects are both either positive or negative predictors of the outcome) or asymmetric (both are present, but with opposite signs). An example of symmetric bidirectionality is reported in Hong et al. (2005). In couples in which one partner was a cardiac rehabilitation patient and the other partner was the undiagnosed spouse, the same partner effects were observed for both patients and spouses. Spouse's social support given to their diagnosed partner (i.e., the patient) about exercise predicted patient's social support received; Patient's social support given to their undiagnosed partner about exercise predicted spouse's social support received (Hong et al., 2005). Therefore, these couples' dyadic exchanges of support to exercise were effective, such that both partners' support given was perceived by the other partner as support received. In this example, the bidirectional influences of support may transcend the diagnosis, meaning that although other relationship processes may undergo necessary (and even, perhaps, detrimental) change due to the effects of the diagnosis, many pre-existing and positive relationship processes (e.g., social support to exercise) may continue to be effective and bidirectional in nature, despite the effects of the diagnosis. Some newly-diagnosed DU couples may worry that bidirectional relationship processes, such as their communication, problem-solving abilities, or parenting decisions, may be negatively influenced by the diagnosis. Therefore, it is important to identify which bidirectional processes are preserved and which are negatively impacted by a diagnosis to better inform therapists, counselors, and practitioners about which relational processes could be capitalized on as a form of couples' strength, versus those that may warrant extra attention when couples are adjusting to a new diagnosis or to a different stage within the diagnosis.

An example of lack of bidirectionality is reported in Knoll et al. (2009), who examined the transmission of stress appraisals and depression symptoms across romantic partners

who were both undergoing assisted-reproduction treatment (a DD study). These researchers found transmission of stress appraisals and of depression symptoms, but only in the direction of men transmitting to women and not *vice versa*. Often depression and stress are thought of as within-person phenomena, however, these findings suggest that one way to improve women's depression and stress appraisals may be to enhance their awareness of how their partners' depression and stress may be affecting them. Another example of lack of bidirectionality in partner effects is reported in Kim et al. (2008). Interestingly, mothers' psychological distress predicted their caregiving daughters' quality of life, but the reverse was not true (Kim et al., 2008). These asymmetrical partner effects suggest that the daughters may have made an effort to regulate their own distress so that it did not impact (or transmit to) their mothers. The absence of bidirectionality in these examples is important in that different factors may better predict outcomes for diagnosed and undiagnosed partners, or for men and women. Essentially, some models (i.e., certain predictor variables) may be better matched to one member's outcome variable, but not the other member. Therefore, knowing that the mother's distress is affecting the daughter's quality of life (or the men's depression is affecting their female partners), but not *vice versa*, suggests that intervening with the mother's distress (or the men's depression), rather than the daughter's distress (or wives' depression), may be more beneficial for their interdependent relationship and qualities of life.

Kenny and Ledermann (2010) k parameter may prove to be a useful way to measure these different types of bidirectionality. The parameter k measures the ratio of partner to actor effect, assuming the actor effect is nonzero. When k equals one, we have a couple model, when k equals zero, we have actor only model, and when k equals minus one, we have a contrast model. For instance, for Klumb et al. (2006), k is very near minus one such that the more household labor you do relative to your spouse, the higher your cortisol level.

Asymmetry in Y intercepts

One important question that is particularly relevant to DU studies is whether or not there is asymmetry in the Y intercepts, or the predicted average score on the outcome variable, between the diagnosed and undiagnosed partners. For example, mothers with cancer may report higher, lower, or the same quality of life as their adult caregiving daughters. Almost always, there are mean differences on Y between the diagnosed and undiagnosed members of the dyad, likely because the outcome variable is often related to physical and/or mental health and it is practical to assume that health scores may differ between the diagnosed and undiagnosed member of the dyad. Indeed, in Kim et al. (2008), survivors of cancer reported poorer physical health than their adult caregiving daughters. Additionally, diagnosed and undiagnosed members of a dyad may also differ on outcome variables other than physical health, but that are related to it. These differences in variables other than physical health are often of particular interest, in which case physical health would need to be controlled for in order to show that individuals differ on these outcomes *after* controlling for differences in their health.

Asymmetry in error variances in Y

Another important consideration, especially in DU studies, is to test for asymmetry in the error variances in Y (i.e., prediction errors for the outcome) for the two members of the dyad. It is unlikely that the predictor (X) variables will explain all of the variance in the dependent variables (Y); Therefore, the extent to which Y_1 and Y_2 are not explained by

X_1 or X_2 is represented by the residual or error terms for both members' Y variables (Cook & Kenny, 2005). The error variance for each member of the dyad represents the effect of all the unmeasured potential predictor variables that have not been included in the equation, as well as errors of measurement (Cook & Kenny, 2005). The error variance is important because it helps to inform us about how well we are predicting one or the other partner. In other words, asymmetry in the error variances for Y is indicative of a difference in model fit for the members. This difference may also indicate that the mechanisms (i.e., the actor and partner effects) are asymmetric for the members. Actor or partner effects for one partner, but not for the other, is evidence that an actor-partner model predicts the former partner better than the latter. It is therefore important to consider if, theoretically, the model is sensible for predicting *both* members of the dyad.

The issue of asymmetric error variances is especially critical in DU studies because some variables may not apply to both partners equally. As an example, imagine a sample of couples in which the wives have breast cancer and their male partners are undiagnosed. Say, for example, that we want to predict how distressed the patients and their spouses are from their experiences of chemotherapy treatment. This model might do an excellent job of predicting the patients' distress, but might not predict the spouses' distress very well, because the patients are physically impacted by every chemotherapy session but the spouses may not attend all of them, and if they do, they are only indirectly influenced. Therefore, the spouses' level of reported distress may not be nearly as much influenced by the chemotherapy treatment as the patients' level, producing asymmetry in the error variances in Y for diagnosed and undiagnosed partners. Reporting this asymmetry is an important first step to determine if and how the model should be changed to better estimate both partners' outcomes.

Most of the DU studies reviewed did not explicitly test or report asymmetry in the error variances. However, one study did report the percentage of variance that the patient's model and spouse's model accounted for with various outcome variables (Kershaw et al., 2008). The proposed model examined factors that promoted the use of active coping strategies, as well as the effect of these coping strategies on quality of life, for patients with prostate cancer and their undiagnosed spouses (Kershaw et al., 2008). Interestingly, the model predicting active coping accounted for 19% of the variance of patient coping and only 10% of the variance of spouse coping. Active coping was relevant to the patients, such that various individual and family factors did predict patients' active coping, and patients' active coping predicted their own quality of life. There were no direct paths, however, either *to* active coping or *from* active coping to quality of life for spouses, which indicated that nothing predicted spouses' active coping, and spouses did not necessarily use active coping to maintain or enhance their quality of life (Kershaw et al., 2008). Therefore, the patients' and spouses' error variances reflect the misfit of the model for each of them and can inform future models (and guide theories) that better predict both patients' and spouses' outcomes. Importantly, however, in this example, we are assuming that 19% of the explained variance for patients is more than the 10% of the explained variance for spouses. However, a higher percentage of variance explained is not always better – particularly if there is less variance to explain in the first place (or if we consider absolute variance). Similarly, although error variance is often thought of with a negative connotation, more error variance may also mean more “action” and more room for future investigation. For example, if you study quality of life as an outcome in a patient-caregiver study, and you find substantial error variance in quality of life for the patient, but not for the caregiver (i.e., asymmetry in error variances), then your attention can be focused on further exploring the underlying mechanisms for the patient.

Including a UU control group

An important methodological consideration for DD and DU studies is the inclusion of a control group composed of UU dyads. In the context of a DD study, this would allow researchers to examine if the actor and partner effects are stronger or weaker in DD versus UU couples. For example, in most studies of couples undergoing assisted reproduction treatment (DD), a UU control group has not been used. However, the addition of such a group can provide interesting insights into whether DD couples are especially prone to transmitting stress and depressive symptoms to their partners due to their situation, or if instead they are resilient and transmit less (or the same) stress and depressive symptomology as UU couples. Perhaps DD couples are at a particular advantage over UU couples for improving each other's health and well-being because they are undergoing similar experiences (e.g., involuntary childlessness) in which they may more readily turn to each other for support and collaborative dyadic coping (Bodenmann, 1997). It is important to explore these possibilities by including UU couples in DD studies.

Similarly, the addition of a control group in DU studies would allow researchers to examine how undiagnosed partners in DU couples, especially those that do not differ on their *Y* intercepts from their diagnosed partners, compare to individuals in couples completely free of the diagnosis. This would address the important question of whether the undiagnosed partners in DU couples have poorer health than those in couples untouched by the diagnosis. For example, Kim et al. (2008) found that both survivors of cancer and their adult caregiving daughters did not differ on mental health scores. This lack of asymmetry in *Y* intercepts may be due to many different mechanisms. Three possible mechanisms include: (1) perhaps the cancer diagnosis did not impact the survivor's mental health, such that her mental health has remained similar to her daughter's mental health; (2) the survivor's diagnosis impacted both her own and her daughter's mental health, such that they both have experienced similar declines in mental health; or (3) the daughter's mental health impacted the survivor's mental health, such that the survivor's mental health has been buffered by her daughter. To differentiate between these three possibilities requires knowledge of population norms for the mental health measure, which could be gained by including a UU control group, and patterns of actor and partner effects. For example, there would be evidence for the first possibility if both partners had similar mental health scores to the UU control group, and if there was *no* evidence of actor or partner effects (because the diagnosis did not have any effect on either member). There would be evidence for the second possibility if both partners had lower mental health scores than the UU control group, and if there was evidence of a mother actor effect (i.e., the mothers' diagnosis affects her own mental health), and a mother to daughter partner effect (i.e., the mother's diagnosis impacts the daughter's mental health). Finally, there would be evidence for the third possibility if both partners had similar mental health scores to the UU control group, and if there was evidence of a daughter to mother partner effect (i.e., the daughter's mental health affects her mother's mental health). Therefore, UU control groups, which can provide a proxy for population norms, and the patterns in actor and partner effects, are important pieces of information to acquire to uncover the mechanistic and process-level differences between the two members of the dyad.

A few studies have included a mix of UU, DU, and DD couples, allowing them to address substantive questions such as: What is the effect of the disease (or the diagnosis status) on the behavior and perceptions of each partner? And, how might these behaviors and perceptions compare across the different configurations of couple type? The few

studies that have included a mix of couple-types present some interesting answers to these questions. For example, couples in which one, both, or neither gay partner had HIV differed in their agreements to allow sex with outside partners (Hoff et al., 2009). Monogamous agreements were reported by 56% of the couples in which both partners had negative HIV statuses, 47% of the couples in which both partners had positive HIV statuses, and 36% of the couples in which one member had HIV and the other did not (i.e., discordant relationships). Furthermore, agreement quality (i.e., how much each member valued, was committed to, and was satisfied with the agreement) was the lowest among men in discordant relationships. In other examples, couples in which both partners smoked reported *increased* positive emotion and emotional synchrony when smoking together, whereas partners in couples where only one person smoked reported *decreased* positive emotion and synchrony when their partner lit up (Rohrbaugh et al., 2009; Shoham et al., 2007). Lastly, Markey and Markey (2011) examined the effects of body mass index (BMI) status on the weight concerns of romantic partners who varied in BMI. When individuals had low BMIs (i.e., normal/healthy), their partner's BMI had little relation to their own weight concerns; However, individuals who had high BMIs, and were in a relationship with individuals maintaining low BMIs, were at particular risk for having high levels of weight concerns. These findings illustrate that perhaps discordant relationships (one member has HIV or smokes or has a high BMI and the other member does not) may be the most at risk for experiencing more relationship- or health-oriented concerns due to diagnosis.

However, findings from one DU versus UU study suggest the contrary. Downey et al. (1999) studied mothers who experienced heightened anger due to chronic pain from RSDS, mothers without RSDS, and their respective undiagnosed adolescent children. Downey et al. (1999) observed that the transmission of mother's anger to their children was actually reduced in families that included an RSDS mother. One possible explanation is that the mothers with RSDS may have been less likely than control mothers to attribute their anger to actions of their child, and rather may have been better equipped to realize the role of pain in their anger and to regulate their own anger expression (Downey et al., 1999). In summary, there is no one pattern that emerges in these studies as to the effects of a diagnosis on the behaviors and perceptions of each partner in different dyadic configurations (UU, DU, and DD). Rather, this complex context warrants future research using the dyadic configuration as a moderator in order to explore how behaviors and perceptions differ for each type and under what conditions concordant versus discordant dyads are at greater health risk or benefit.

Examining mediation

Very often, researchers have an interest in the causal process that occurs when studying dyads. For instance, Manne et al. (2012) examined how positive spousal communication in couples where one partner has lung cancer or head and neck cancer may reduce partners' distress, due to greater intimacy. "Simple" mediation requires three variables, *X* or the causal variable, *M* or the mediator, and *Y* the outcome. In the previous example, spousal communication is *X*, intimacy is *M*, and distress is *Y*. The idea of mediation is that *M* explains the association between *X* and *Y*.

Following Ledermann, Macho, and Kenny (2011), the measurement of mediation within the APIM is rather complex. There are potentially four different indirect effects: actor-actor, partner-partner, actor-partner, and partner-actor. So for instance, a partner-partner indirect effect would be a partner effect from *X* to *M* and a partner effect from

M to *Y*. Each of these four types of indirect effects can be obtained for each member of the dyad (e.g., *D* and *U*), resulting in up to eight different types of indirect effects. These eight indirect effects explain four effects: The actor and partner effects from *X* to *Y* for each of the two members. Actor effects are explained by actor-actor and partner-partner indirect effects and partner effects are explained by actor-partner and partner-actor indirect effects. The task of the researcher is to find some way to simplify these different indirect effects. The interested reader should consult Ledermann et al. (2011) for guidance on this issue.

An extension of the mediation model is moderated mediation. Moderation is typically assessed by an interaction between the causal variable (*X*) and another variable called the moderator; if mediation is moderated, then mediation is stronger for one group (e.g., diagnosed partners) than another (e.g., undiagnosed partners). Moderated mediation within the APIM is a very advanced topic; however, interested readers can consult various resources that discuss moderated mediation and mediated moderation in more detail (Bauer, Preacher, & Gil, 2006; Edwards & Lambert, 2007; Muller, Judd, & Yzerbyt, 2005). Lastly, to strengthen the claims of causality that are necessary in the study of mediation, over-time studies can be employed, a topic we now turn our attention to.

Including time

When studying dyads, partner effects are of paramount importance because they may be evidence of a larger systemic process in which the presence of another person (e.g., a partner) results in a change in some other individual. Furthermore, the effects of predictors may not remain constant over time, especially for interdependent partners, and one of the primary concerns in health research is to understand changes in well-being over time. Therefore, introducing *time* allows researchers to assess partners' health relevant change and flexibility (or inflexibility). Although many researchers employ cross-sectional designs, such that participants report a score on their *X* and *Y* variables only once, there is a growing body of dyadic longitudinal research. Studies that have multiple time points per variable, per person, can indeed better address the dynamic aspects of health and social relationships.

Dyadic longitudinal designs can take many forms, including daily-dairy studies (Badr et al., 2010; Berg et al., 2011; Fagundes et al., 2012), intervention studies (Holt-Lunstad et al., 2008; Porter et al., 2009), or repeated physiological assessments (Saxbe & Repetti, 2010). However, there are many challenges associated with incorporating time into a dyadic design. We may have lofty hopes of conducting longitudinal dyadic studies with the notion that we can run a growth curve analysis to determine if baseline characteristics had effects over time, or to see if intervention effects were maintained over time. However, sometimes key predictors (other than "time") are time-varying as well, and these may be important to include in the model. For example, in addition to examining how partners' infertility-related distress changes over the course of 5 years while undergoing unsuccessful fertility treatment, it may also be important to explore how changes in coping strategies predict changes in distress over time. Additionally, although a growth curve analysis can model change that occurs in a linear or exponential fashion, this analysis may not be appropriate if the outcome is cyclical or sinusoidal in nature, such as the ebb and flow of partners' emotional affect over a 2-week period when coping with cancer (Berg et al., 2011), or the within-dyad covariation between salivary cortisol and emotional affect for healthy couples (Saxbe & Repetti, 2010).

Lagged analyses present another possible model that researchers may use to examine change over time. Lagged analyses take into account the fundamental principles that an outcome variable is caused by prior values of the same outcome variable, and that an outcome variable is caused by prior values of different variables (Gollob & Reichardt, 1987). As such, lagged analyses are one effective way to examine the degree to which variables in the past, say $t - 1$, predict an outcome in the present, t . An even stronger lagged model would control for the outcome in the past, $t - 1$, as well. Badr et al. (2010) employed a lagged analysis to examine how metastatic breast cancer (MBC) patients' pain affected couples' relationship functioning. Couples completed electronic diaries for 14 consecutive days in which they rated the MBC patient's pain and the intensity of their own mood six times a day (once in the morning, four times in the afternoon, and once in the evening), and perceptions of relationship functioning once in the evening. In one of their models, the authors found that greater MBC patient pain in the morning was associated with lower levels of MBC patient aroused mood during the day, while controlling for MBC patient mood in the morning. Therefore, it is important to, whenever possible, control for the previous level of the outcome variable to conduct a more rigorous test of change over time.

Lagged models do, however, pose some challenges. For example, imagine a physiological linkage model in which partner A's current cortisol is predicted by partner B's prior cortisol, while controlling for partner A's prior cortisol. It is likely that the two predictors (i.e., partner B's prior cortisol and partner A's prior cortisol) are highly correlated with each other. This high correlation may introduce multicollinearity, which may ultimately increase the probability of committing a Type II error. In this instance, it may be more beneficial to use a concurrent model, rather than a lagged model. An additional challenge of lagged analyses is having enough time points that are appropriately spaced to observe the phenomenon of interest. Because collecting longitudinal data is time- and effort-intensive, it is critical that we have a solid theoretical understanding of how often, and in what way, we expect change over time in *both* the outcome(s) and predictor(s). This will inform the sampling approach of how many follow-up assessments to collect and the length of time between assessments. We suggest that researchers assess no fewer than three time points. Two time points is insufficient for a number of reasons; one primary reason is that two time points, by default, provide only *linear* information over time (Singer & Willett, 2003). Often it is the case that the behaviors and health that we are interested in are actually curvilinear, exponential, or sinusoidal, and therefore, multiple measurements (ideally more than three) are needed. Determining the adequate length of time between assessments, in order to detect change over time, also requires careful thought. Berg et al. (2011) theorized that couples coping with prostate cancer experience daily stressful events (e.g., incontinence and impotence) that may influence daily increases or decreases in negative and positive affect. As such, they employed a daily diary methodology. Again, employing a theory or guiding framework is paramount when making these decisions. Lastly, *when* to collect measurements is also an important consideration; this is particularly true for physiological data, such as cortisol. For example, it is typical to measure cortisol multiple times per day (e.g., upon waking, just before lunch, early evening, and evening before bed, etc.) to account for diurnal effects (Holt-Lunstad et al., 2008; Saxbe & Repetti, 2010).

Many other challenges inherently plague longitudinal research and the associated analyses, including: power considerations, test effects, attrition, and causal inferences. When determining power, some researchers may wrestle with whether they should increase the number of people in their study, or increase the number of measurements over time.

Ultimately, the answer to this question should be guided by theory and prior research. A certain method (i.e., increasing participants or increasing assessments) may be better, depending on whether a *between* or *within* person phenomenon is being investigated. Between-person phenomena may require more participants and within-person phenomena may require more time points per person. Determining power for longitudinal dyadic studies is complex, however, and researchers can turn to other articles for further explanation of this issue (Maxwell, 1998; Scherbaum & Ferreter, 2009).

Often in longitudinal designs, we ask participants to answer the same questions many times, often within a short time frame (e.g., daily diaries). It is likely that this can contribute to several effects, including reactance, habituation, and increased awareness of the construct being measured (Bolger, Davis, & Rafaeli, 2003). Although these effects are hard to avoid, it is often possible to assess their presence by checking for main effects of time. For example, habituation may result in linearly decreasing scores, which could then be controlled for when assessing focal predictors. Attrition also often occurs in longitudinal health research due to a variety of issues, including: patient death (Manne et al., 2012; Peterson et al., 2009), feeling too ill to continue (Manne et al., 2012), an illness in the family (Berg et al., 2011; Fagundes et al., 2012), or patient illness (Porter et al., 2009). It is important to determine and report if and how the participants who completed the study were different from participants who dropped out. For example, Manne et al. (2012) reported that participants who completed the study had a higher income and had partners who were more open with regard to sharing their concerns about the effects of cancer on their lives. This information can be valuable for sampling purposes for future studies (e.g., purposely sample lower socio-economic populations or couples that may be more hesitant to discuss their concerns). Lastly, although the effect of attrition may affect study results and conclusions, there are ways of dealing with missing data that ensues, depending on the amount and kind of missingness (e.g., missing at random). Interested readers can consult various readings on how to identify and deal with missing data (Graham, 2009; Schlomer, Bauman, & Card, 2010).

Although a longitudinal design is more robust than a cross-sectional design for making inferences about cause and effect, it is important to emphasize that a longitudinal (non-experimental) design is still not a causal design. Again, having a theory or guiding framework is crucial in rationalizing whether the predictor(s) temporally occurs before the outcome, and if there are any third variables that may be causing the observed association. Rigorous analyses that incorporate time-lags can help to address these concerns. For example, Badr et al. (2010) hypothesized a causal mechanism that MBC patient mood mediated the effects of patient pain on couples' relationship functioning. As such, they used a model in which *X* (MBC patient pain) was measured earlier in time from the mediator, *M* (patient aroused mood), and *M* was measured earlier in time from *Y* (relationship functioning). Ultimately, they tested an ideal time-lag design in which patient pain, reported in the morning, predicted relationship functioning, reported in the evening, as mediated by patient aroused mood, reported in the afternoon (Badr et al., 2010). Having a well thought-out design and rigorous analysis, such as this, makes it very plausible that the predictors indeed preceded the outcome.

Including time creates a plethora of new and important dyadic interrelations to be investigated. For example, the phenomenon of physiological linkage (covariation of partners' physiological indices) could not be studied with a cross-sectional design. In addition, including time, in the form of a longitudinal study, would allow researchers to examine the transition from a UU study to a DU study. Admittedly, the analysis of longitudinal data from dyads is complex, but information and software tools have become more

readily available. Interested readers can consult various resources for a more in-depth discussion of longitudinal dyadic data analysis and of analyses that employ a dynamic systems perspective to examine dyadic transactional processes (Butler, 2011; Kenny et al., 2006; Laurenceau & Bolger, 2005). Ultimately, relationship partners of all sorts will continue to experience complex dyadic interactions together in health-relevant contexts. Therefore, making use of time-varying dyadic data designs is a critical future direction for understanding couples as interdependent dynamic systems with inter-connected, changing health processes.

Conclusion

Given that individuals' health may influence their social relationships, and that romantic partners, parents, children, and many others play a fundamental role in promoting their partners' health and well-being, the application of dyadic data to all areas of health research has great potential. The purpose of this paper was to clarify and highlight some of the methodological and substantive considerations that researchers may want to focus on when preparing for and tackling their own dyadic research. We hope that the reader shares some of our excitement about the wide array of interesting questions that can now be addressed using dyadic models. We feel the door has only recently been opened and we have yet to enter into a room of the vast possibilities of exciting inter-personal discoveries concerning health and well-being.

Short Biographies

Rebecca G. Reed is a doctoral student in the Family Studies and Human Development division at the University of Arizona. She holds a B.S. in Physiology and an M.S. in Family Studies and Human Development from the University of Arizona. Her current research involves dyadic methodologies to investigate how emotion regulation interacts with physiological processes and health of romantic partners. A forthcoming publication reports on an empirical investigation of partner influence on physiological linkage of autonomic physiology measures in couples.

Emily A. Butler is an Associate Professor in the Family Studies and Human Development division at the University of Arizona. Her research focuses on emotional, self-regulatory and relationship mechanisms that contribute to physical and mental health. To guide this research she has developed a model of interpersonal emotion systems, which involve the dynamic interaction of emotion components (subjective experience, expressive behavior, physiology) within and between partners over time during social interactions and in close relationships. Her recent publications include empirical investigations of conflict in mixed-weight couples (e.g. one healthy weight partner and one overweight partner) and the daily effects of emotion suppression on eating, as well as theoretical review papers on coregulation as a form of interpersonal emotion regulation and temporal interpersonal emotion systems. Butler completed her BA in Psychology at Simon Fraser University in Canada, her PhD in Psychology at Stanford, and a Post-Doctoral research fellowship in Psychology at the University of Arizona.

David A. Kenny is a Distinguished Alumni and Board of Trustees Professor at the University of Connecticut. His PhD is from Northwestern University where he studied with Donald T. Campbell. His research focuses on dyadic data analysis, models of mediation and moderation, the DataToText project, and interpersonal perception. He has written six books, the most recent being *Dyadic Data Analysis* with D. Kashy and W. Cook.

Endnote

* Correspondence address: Division of Family Studies and Human Development, 650 North Park Ave., University of Arizona, Tucson, AZ 85721-0078, USA. Email: rgreed@email.arizona.edu

References

- Badr, H., Laurenceau, J. P., Schart, L., Basen-Engquist, K., & Turk, D. (2010). The daily impact of pain from metastatic breast cancer on spousal relationships: A dyadic electronic diary study. *Pain*, **151**, 644–654.
- Bagozzi, R. P., Ascione, F. J., & Mannebach, M. A. (2005). Inter-role relationships in hospital-based pharmacy and therapeutics committee decision making. *Journal of Health Psychology*, **10**, 45–64.
- Baider, L., Andritsch, E., Goldzweig, G., Uziely, B., & Ever-Hadani, P. (2004). Changes in psychological distress of women with breast cancer in long-term remission and their husbands. *Psychosomatics*, **45**, 58–68.
- Bauer, D. J., Preacher, K. J., & Gil, K. M. (2006). Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: New procedures and recommendations. *Psychological Methods*, **11**, 142–163.
- Belcher, A. J., Laurenceau, J. P., Graber, E. C., Cohen, L. H., Dasch, K. B., & Siegel, S. D. (2011). Daily support in couples coping with early stage breast cancer: Maintaining intimacy during adversity. *Health Psychology*, **30**, 665–673.
- Berg, C. A., Wiebe, D. J., & Butner, J. (2011). Affect covariation in marital couples dealing with stressors surrounding prostate cancer. *Gerontology*, **57**, 167–172.
- Bloom, J. R. (1982). Social support, accommodation to stress and adjustment to breast cancer. *Social Science & Medicine*, **16**, 1329–1338.
- Bodenmann, G. (1997). Dyadic coping: A systemic-transactional view of stress and coping among couples: Theory and empirical findings. *European Review of Applied Psychology*, **47**, 137–141.
- Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology*, **54**, 579–616.
- Butler, E. A. (2011). Temporal interpersonal emotion systems: The “TIES” that form relationships. *Personality and Social Psychology Review*, **15**, 367–393.
- Butterfield, R. M., & Lewis, M. A. (2002). Health-related social influence: A social ecological perspective on tactic use. *Journal of Social and Personal Relationships*, **19**, 505–526.
- Cook, W. L., & Kenny, D. A. (2005). The Actor–Partner Interdependence Model: A model of bidirectional effects in developmental studies. *International Journal of Behavioral Development*, **29**, 101–109.
- Dorros, S. M., Card, N. A., Segrin, C., & Badger, T. A. (2010). Interdependence in women with breast cancer and their partners: An interindividual model of distress. *Journal of Consulting and Clinical Psychology*, **78**, 121–125.
- Dorval, M., Guay, S., Mondor, M., Masse, B., Falardeau, M., Robidoux, A. et al. (2005). Couples who get closer after breast cancer: Frequency and predictors in a prospective investigation. *Journal of Clinical Oncology*, **23**, 3588–3596.
- Downey, G., Purdie, V., & Schaffer-Neitz, R. (1999). Anger transmission from mother to child: A comparison of mothers in chronic pain and well mothers. *Journal of Marriage and the Family*, **61**, 62–73.
- Driscoll, K. A., Schatschneider, C., McGinnity, K., & Modi, A. C. (2012). Application of dyadic data analysis in pediatric psychology: Cystic fibrosis health-related quality of life and anxiety in child–caregiver dyads. *Journal of Pediatric Psychology*, **37**, 605–611.
- Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. *Psychological Methods*, **12**, 1–22.
- Fagundes, C. P., Berg, C. A., & Wiebe, D. J. (2012). Intrusion, avoidance, and daily negative affect among couples coping with prostate cancer: A dyadic investigation. *Journal of Family Psychology*, **26**, 246–253.
- Gellert, P., Ziegelmann, J. P., Warner, L. M., & Schwarzer, R. (2011). Physical activity intervention in older adults: Does a participating partner make a difference? *European Journal of Ageing*, **8**, 211–219.
- Gollob, H. F., & Reichardt, C. S. (1987). Taking account of time lags in causal models. *Child Development*, **58**, 80–92.
- Graham, J. W. (2009). Missing data analysis: Making it work in the real world. *Annual Review of Psychology*, **60**, 549–576.
- Hoff, C. C., Chakravarty, D., Beougher, S. C., Darbes, L. A., Dadasovich, R., & Neilands, T. B. (2009). Serostatus differences and agreements about sex with outside partners among gay male couples. *AIDS Education and Prevention*, **21**, 25–38.
- Holt-Lunstad, J., Birmingham, W. A., & Light, K. C. (2008). Influence of a “warm touch” support enhancement intervention among married couples on ambulatory blood pressure, oxytocin, alpha amylase, and cortisol. *Psychosomatic Medicine*, **70**, 976–985.
- Hong, T. B., Franks, M. M., Gonzalez, R., Keteyian, S. J., Franklin, B. A., & Artinian, N. T. (2005). A dyadic investigation of exercise support between cardiac patients and their spouses. *Health Psychology*, **24**, 430–434.
- Kenny, D. A. (1996). The design and analysis of social-interaction research. *Annual Review of Psychology*, **47**, 59–86.

- Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). *Dyadic Data Analysis*. New York, NY: The Guilford Press.
- Kenny, D. A., & Ledermann, T. (2010). Detecting, measuring, and testing dyadic patterns in the Actor-Partner Interdependence Model. *Journal of Family Psychology*, **24**, 359–366.
- Kenny, D. A., Veldhuijzen, W., Weijden, T., LeBlanc, A., Lockyer, J., Légaré, F. et al. (2010). Interpersonal perception in the context of doctor-patient relationships: A dyadic analysis of doctor-patient communication. *Social Science & Medicine*, **70**, 763–768.
- Kershaw, T. S., Mood, D. W., Newth, G., Ronis, D. L., Sanda, M. G., Vaishampayan, U. et al. (2008). Longitudinal analysis of a model to predict quality of life in prostate cancer patients and their spouses. *Annals of Behavioral Medicine*, **36**, 117–128.
- Kiecolt-Glaser, J. K., & Newton, T. L. (2001). Marriage and health: His and hers. *Psychological Bulletin*, **127**, 472–503.
- Kim, Y., Wellisch, D. K., & Spillers, R. L. (2008). Effects of psychological distress on quality of life of adult daughters and their mothers with cancer. *Psycho-Oncology*, **17**, 1129–1136.
- Klumb, P., Hoppmann, C., & Staats, M. (2006). Work hours affect spouse's cortisol secretion—for better and for worse. *Psychosomatic Medicine*, **68**, 742–746.
- Knoll, N., Schwarzer, R., Pfüller, B., & Kienle, R. (2009). Transmission of depressive symptoms: A study with couples undergoing assisted-reproduction treatment. *European Psychologist*, **14**, 7–17.
- Kurtz, M. E., Kurtz, J. C., Given, C. W., & Given, B. A. (2004). Depression and physical health among family caregivers of geriatric patients with cancer—a longitudinal view. *Medical Science Monitor*, **10**, 447–456.
- Laurenceau, J. P., & Bolger, N. (2005). Using diary methods to study marital and family processes. *Journal of Family Psychology*, **19**, 86–97.
- Ledermann, T., & Kenny, D. A. (2012). The common fate model for dyadic data: Variations of a theoretically important but underutilized model. *Journal of Family Psychology*, **26**, 140–148.
- Ledermann, T., Macho, S., & Kenny, D. A. (2011). Assessing mediation in dyadic data using the Actor-Partner Interdependence Model. *Structural Equation Modeling*, **18**, 595–612.
- Ledyard, M. L., & Morrison, N. C. (2008). The meaning of weight in marriage: A phenomenological investigation of relational factors involved in obesity. *Journal of Couple & Relationship Therapy*, **7**, 230–247.
- Lee, S., Colditz, G. A., Berkman, L. F., & Kawachi, I. (2003). Caregiving and risk of coronary heart disease in US women: A prospective study. *American Journal of Preventive Medicine*, **24**, 113–119.
- Mahaffey, K. J., & Marcus, D. K. (2006). Interpersonal perception of psychopathy: A social relations analysis. *Journal of Social and Clinical Psychology*, **25**, 53–74.
- Manne, S. L., Badr, H., & Kashy, D. A. (2012). A longitudinal analysis of intimacy processes and psychological distress among couples coping with head and neck or lung cancers. *Journal of Behavioral Medicine*, **35**, 334–346.
- Manne, S. L., Pape, S. J., Taylor, K. L., & Dougherty, J. (1999). Spouse support, coping, and mood among individuals with cancer. *Annals of Behavioral Medicine*, **21**, 111–121.
- Markey, C., & Markey, P. (2011). Romantic partners, weight status, and weight concerns: An examination using the Actor-Partner Interdependence Model. *Journal of Health Psychology*, **16**, 217–225.
- Maxwell, S. E. (1998). Longitudinal designs in randomized group comparisons: When will intermediate observations increase statistical power? *Psychological Methods*, **3**, 275–290.
- McMahon, J. M., Pouget, E. R., & Tortu, S. (2007). Individual and couple-level risk factors for hepatitis C infection among heterosexual drug users: A multilevel dyadic analysis. *Journal of Infectious Diseases*, **195**, 1572–1581.
- Mellon, S., Kershaw, T. S., Northouse, L. L., & Freeman-Gibb, L. (2007). A family-based model to predict fear of recurrence for cancer survivors and their caregivers. *Psycho-Oncology*, **16**, 214–223.
- Muller, D., Judd, C. M., & Yzerbyt, V. Y. (2005). When moderation is mediated and mediation is moderated. *Journal of Personality and Social Psychology*, **89**, 852–863.
- Northouse, L. L. (1988). Social support in patients' and husbands' adjustment to breast cancer. *Nursing Research*, **37**, 91–95.
- Northouse, L., Williams, A., Given, B., & McCorkle, R. (2012). Psychosocial care for family caregivers of patients with cancer. *Journal of Clinical Oncology*, **30**, 1227–1234.
- Peterson, B., Pirritano, M., Christensen, U., Boivin, J., Block, J., & Schmidt, L. (2009). The longitudinal impact of partner coping in couples following 5 years of unsuccessful fertility treatments. *Human Reproduction*, **24**, 1656–1664.
- Porter, L. S., Keefe, F. J., Baucom, D. H., Hurwitz, H., Moser, B., Patterson, E. et al. (2009). Partner-assisted emotional disclosure for patients with gastrointestinal cancer. *Cancer*, **115**, 4326–4338.
- Preacher, K. J., Curran, P. J., & Bauer, D. J. (2006). Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis. *Journal of Educational and Behavioral Statistics*, **31**, 437–448.
- Rohleder, N., Marin, T. J., Ma, R., & Miller, G. E. (2009). Biologic cost of caring for a cancer patient: Dysregulation of pro-and anti-inflammatory signaling pathways. *Journal of Clinical Oncology*, **27**, 2909–2915.
- Rohrbaugh, M. J., Shoham, V., Butler, E. A., Hasler, B. P., & Berman, J. S. (2009). Affective synchrony in dual and single smoker couples: Further evidence of “Symptom System Fit”? *Family Process*, **48**, 55–67.

- Saxbe, D., & Repetti, R. L. (2010). For better or worse? Coregulation of couples' cortisol levels and mood states. *Journal of Personality and Social Psychology*, **98**, 92–103.
- Scherbaum, C. A., & Ferreter, J. M. (2009). Estimating statistical power and required sample sizes for organizational research using multilevel modeling. *Organizational Research Methods*, **12**, 347–367.
- Schlomer, G. L., Bauman, S., & Card, N. A. (2010). Best practices for missing data management in counseling psychology. *Journal of Counseling Psychology*, **57**, 1–10.
- Schulz, R., & Beach, S. R. (1999). Caregiving as a risk factor for mortality. *The Journal of the American Medical Association*, **282**, 2215–2219.
- Shoham, V., Butler, E. A., Rohrbaugh, M. J., & Trost, S. E. (2007). Symptom–System Fit in couples: Emotion regulation when one or both partners smoke. *Journal of Abnormal Psychology*, **116**, 848–853.
- Singer, J. D., & Willett, J. B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. New York, NY: Oxford University Press.
- Uchino, B. N. (2006). Social support and health: A review of physiological processes potentially underlying links to disease outcomes. *Journal of Behavioral Medicine*, **29**, 377–387.
- Uchino, B. N., Uno, D., & Holt-Lunstad, J. (1999). Social support, physiological processes, and health. *Current Directions in Psychological Science*, **8**, 145–148.
- Vitaliano, P. P., Zhang, J., & Scanlan, J. M. (2003). Is caregiving hazardous to one's physical health? A meta-analysis. *Psychological Bulletin*, **129**, 946–972.

Author Query Form

Journal: SPC3

Article: 12022

Dear Author,

During the copy-editing of your paper, the following queries arose. Please respond to these by marking up your proofs with the necessary changes/additions. Please write your answers on the query sheet if there is insufficient space on the page proofs. Please write clearly and follow the conventions shown on the attached corrections sheet. If returning the proof by fax do not write too close to the paper's edge. Please remember that illegible mark-ups may delay publication.

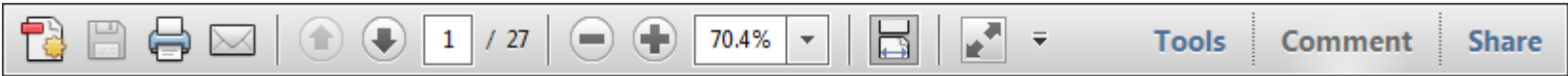
Many thanks for your assistance.

| Query reference | Query | Remarks |
|-----------------|--|---------|
| Q1 | AUTHOR: Kenny and Lederman's (2010) has been changed to Kenny and Ledermann (2010) so that this citation matches the Reference List. Please confirm that this is correct. | |

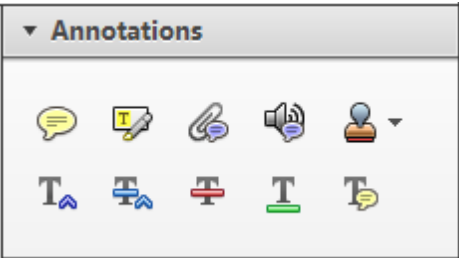
USING e-ANNOTATION TOOLS FOR ELECTRONIC PROOF CORRECTION

Required software to e-Annotate PDFs: Adobe Acrobat Professional or Adobe Reader (version 7.0 or above). (Note that this document uses screenshots from Adobe Reader X)
The latest version of Acrobat Reader can be downloaded for free at: <http://get.adobe.com/uk/reader/>

Once you have Acrobat Reader open on your computer, click on the [Comment](#) tab at the right of the toolbar:



This will open up a panel down the right side of the document. The majority of tools you will use for annotating your proof will be in the [Annotations](#) section, pictured opposite. We've picked out some of these tools below:



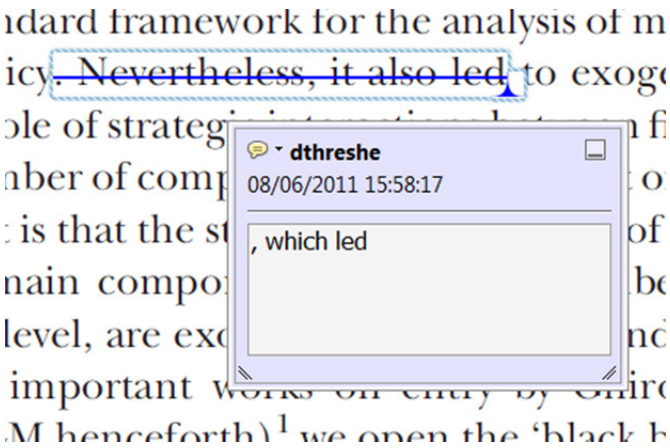
1. [Replace \(Ins\)](#) Tool – for replacing text.



Strikes a line through text and opens up a text box where replacement text can be entered.

How to use it

- Highlight a word or sentence.
- Click on the [Replace \(Ins\)](#) icon in the Annotations section.
- Type the replacement text into the blue box that appears.



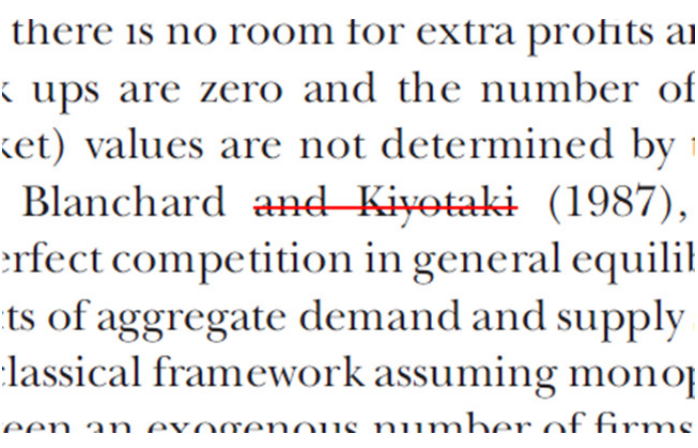
2. [Strikethrough \(Del\)](#) Tool – for deleting text.



Strikes a red line through text that is to be deleted.

How to use it

- Highlight a word or sentence.
- Click on the [Strikethrough \(Del\)](#) icon in the Annotations section.



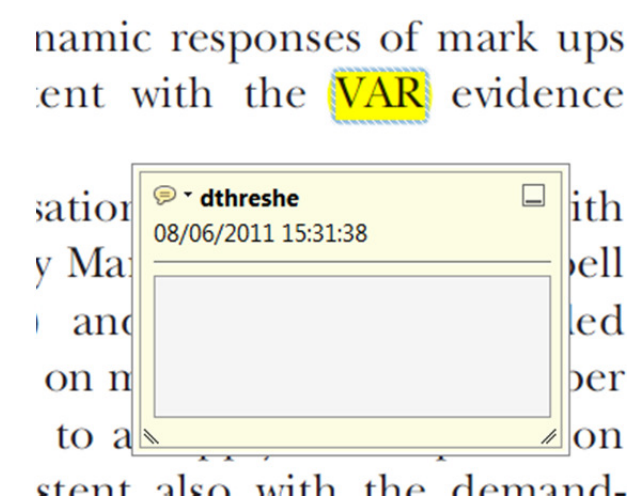
3. [Add note to text](#) Tool – for highlighting a section to be changed to bold or italic.



Highlights text in yellow and opens up a text box where comments can be entered.

How to use it

- Highlight the relevant section of text.
- Click on the [Add note to text](#) icon in the Annotations section.
- Type instruction on what should be changed regarding the text into the yellow box that appears.



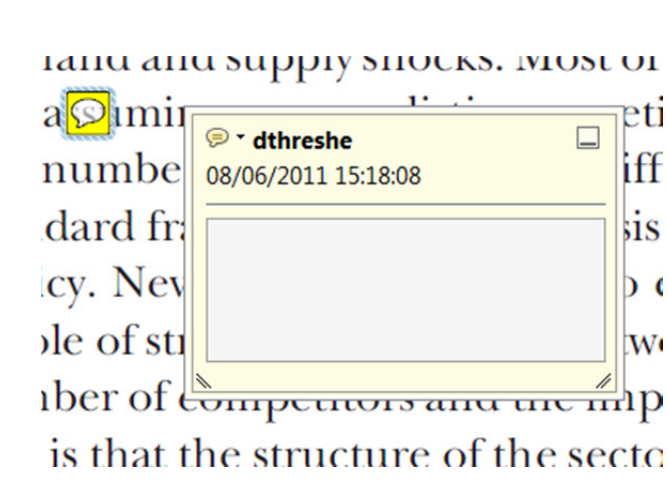
4. [Add sticky note](#) Tool – for making notes at specific points in the text.



Marks a point in the proof where a comment needs to be highlighted.


How to use it

- Click on the [Add sticky note](#) icon in the Annotations section.
- Click at the point in the proof where the comment should be inserted.
- Type the comment into the yellow box that appears.



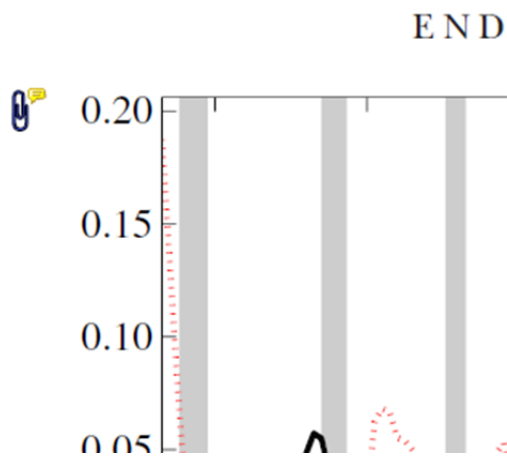
USING e-ANNOTATION TOOLS FOR ELECTRONIC PROOF CORRECTION

5. **Attach File** Tool – for inserting large amounts of text or replacement figures.


 Inserts an icon linking to the attached file in the appropriate place in the text.

How to use it

- Click on the **Attach File** icon in the Annotations section.
- Click on the proof to where you'd like the attached file to be linked.
- Select the file to be attached from your computer or network.
- Select the colour and type of icon that will appear in the proof. Click OK.



6. **Add stamp** Tool – for approving a proof if no corrections are required.

 Inserts a selected stamp onto an appropriate place in the proof.

How to use it

- Click on the **Add stamp** icon in the Annotations section.
- Select the stamp you want to use. (The **Approved** stamp is usually available directly in the menu that appears).
- Click on the proof where you'd like the stamp to appear. (Where a proof is to be approved as it is, this would normally be on the first page).

of the business cycle, starting with the
on perfect competition, constant returns
production. In this environment goods
extra profits and the structure of market
he model. The New-Keynesian model is
etermined by the model. The New-Keynesian
otaki (1987), has introduced product
general equilibrium models with nominal
ad and supply shocks. Most of this literat

APPROVED

Drawing Markups

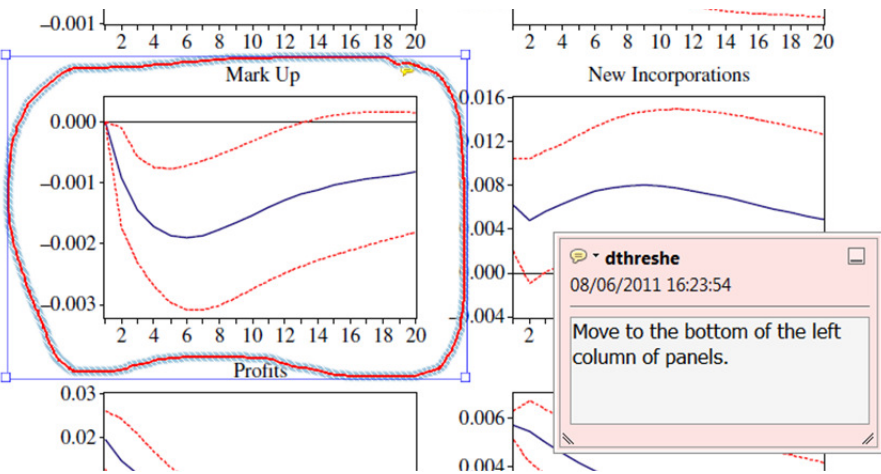


How to use it

- Click on one of the shapes in the **Drawing Markups** section.
- Click on the proof at the relevant point and draw the selected shape with the cursor.
- To add a comment to the drawn shape, move the cursor over the shape until an arrowhead appears.
- Double click on the shape and type any text in the red box that appears.

7. **Drawing Markups** Tools – for drawing shapes, lines and freeform annotations on proofs and commenting on these marks.

Allows shapes, lines and freeform annotations to be drawn on proofs and for comment to be made on these marks..



For further information on how to annotate proofs, click on the **Help** menu to reveal a list of further options:

