Using Dyadic Modeling in Nursing Research: Introduction of Theory and Application

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Abstract

Using dyadic modeling in nursing has theoretical and practical importance as the interpersonal processes related to health behaviors can be captured. Theoretical models focusing on dyadic coping with chronic illness and illness management are established in family nursing. However, few studies utilized dyadic designs in empirical research, while most studies are patient-centric or care partner-centric. With theoretical elaborations and examples, we first review how conventional health models have been extended using a dyadic perspective as well as a brief review of major dyadic frameworks in nursing. Five frequently used dyadic models are described with examples from health and nursing research fields. Statistical applications and cultural considerations are reviewed. We conclude that dyadic modeling provides a useful lens for nursing research but continues to be underutilized.

Keywords: nursing; family nursing; dyadic modeling; dyadic illness management; communal coping

Nursing is a broad research area centering on autonomous and collaborative care provision. Although collaborative care naturally involves dyadic illness management, most studies in nursing tend to focus on the individual level. The word "dyad" literarily denotes a group of two. For patients with chronic illness, the dyadic relationship between the patient and the care partner is commonly observed. To adjust this relationship so as to achieve better health, both dyadic members need to change the way they think and behave; in this way, an illness management involving both members is formed. Theoretical and methodological reconsiderations are needed to encapsulate this management in an interpersonal context.

Purpose

In this article, we review the dyadic modeling approach which derives from personal relationship studies and has been applied in general health research. This article is meant to introduce nursing researchers who have not yet considered incorporating this framework into their research agenda. As dyadic modeling is still a novel approach in nursing, examples in this article also include research from other health fields. With an international perspective, we also illustrate how the dyadic approach could be generalized to behavioral medicine studies in non-Western cultures wherein research is relatively insufficient. We argue that the dyadic approach extends the research practice conventionally held in nursing and provides researchers with a useful toolbox that is compatible with cross-sectional and longitudinal studies.

Literature Review and Integration

Viewing Health and Disease under a Dyadic Framework

Viewing health and disease with an individual lens is a theoretical fashion driven by the biopsychosocial model, which has also served as the foundation of the behavioral medicine (Kenny et al., 2006). Theoretically, both psychophysiological stress and social-cognitive theories that behavioral medicine initially relied on have a strong individualistic ideology. Following this ideology, values such as self-determination have been emphasized whereas interconnectedness and interdependencies in the social context have been downplayed (Lyons & Chamberlain, 2006). As the individual is conceptualized as a cognitive being, people are responsible for their own health and disease (Crawford, 2006). This ideology also translates into individual-level statistical analyses in which health data from one case is treated as independent from others. While increasing findings in nursing field challenged the patient-centric approaches (i.e., focusing primarily on the information or status of the patient while failing to effectively incorporate the care partner–level factors), research and analytic practices such as using single-informant designs continue to be commonplace (Lyons & Lee, 2018).

While the dynamics between the patient and the care partner have been recognized in family nursing practices, these dyadic phenomena were not well reflected in empirical investigations. Imagine the scenario with a patient and a care partner – will the way they appraise and behaviorally manage the illness impact on the health of both dyadic members? The application of such a dyadic view has reformed theories and statistical methods used in nursing. A recent study conducted by Berli et al. (2018) emphasized the importance of acknowledging the dyadic nature in context of physical activity promotion. By utilizing a multilevel approach, the authors showed that both support by the partner in pursuing the goal as well as joint engagement in the goal-related activity, serve as a promising means of increasing levels of physical activity in individuals.

Drawing on work from social-cognitive theories such as the Theory of Planned Behavior (TPB; Ajzen, 1991), one's physical activity can be predicted by one's intention and perceived behavioral control as well as other social constructs (e.g., attitude, subjective norm). However, if a person is in a relationship, the partner may exert additional influences on the person's attitude, subjective norm, and perceived behavioral control. For instance, an athletic partner may constantly provide more pro-exercising information, which, in turn, increases his/her partner's pro-exercising perceptions (e.g., more positive attitudes towards sports). These dynamics, however, may not be sufficiently captured using an individualist approach, neglecting the interpersonal structure a person is embedded in. By extending the individual-level TPB to a dyadic framework, a recent study has highlighted the role of perceived behavioral control and quality of relationship regarding couples' physical activity (Howland et al., 2016). Also based on the TPB, Feng and Wu (2005) previously investigated nurses' intention to report child abuse purely from a nurse-level. Based on the dyadic view, children's appraisal behaviors could also be included to form a multiple-informant framework.

Dyadic Frameworks in the Nursing Research Field

In the past few decades, nursing especially family nursing underwent a critical stage of theoretical reflection, resulting in several useful dyadic frameworks. These models concentrate upon the nature of family system wherein symptom or adjustment is regarded as an outcome of a set of factors within the family and the role of interdependent bonds is emphasized (Cox & Paley, 1997). An early framework about cooperative problem-solving (Lyons et al., 1998) serves as a foundation of subsequent dyadic models in family nursing. In this framework, support and problem-solving for the illness are theoretically extended from an individual level to a communal level (i.e., from *my* problem to *our* problem), thereby the sense of sharing and joining when coping with an illness is emphasized (Lyons et al., 1998).

Based on the communal coping framework, the Theory of Dyadic Illness Management has become its most recent form (Lyons & Lee, 2018). As its name indicates, this model focuses on health of the patient and the care partner in terms of their dyadic management of the illness. It posits that both dyadic appraisals and management behaviors impact on the dyad's physical and mental health (Lyons & Lee, 2018).

Another similar dyadic framework is the developmental-contextual model of couples coping with chronic illness (Berg & Upchurch, 2007), which also centers on dyadic appraisals of illness and dyadic coping. This model focuses on dyadic adjustment to chronic illness that the patient and the care partner both are dealing with. As a model developed for chronic illness management, it also highlights the developmental nature of dyadic adjustment as well as the roles of culture, gender, marital quality, and illness condition (Berg & Upchurch, 2007).

In contrast to the above two models, a recent communal coping and adjustment model (Helgeson et al., 2018; Helgeson & Zajdel, 2017) shows a stronger emphasis on social-cognitive processes of managing an illness. As a model based on the communal coping framework (Lyons et al., 1998), this model also incorporates the functions of dyadic appraisals of illness and dyadic coping behaviors. Moreover, using constructs such as self-efficacy and psychological wellbeing theoretically increases the model's operationalizability. Rather than raising a potential cultural factor that may influence the nursing process, this model specifically includes interdependent self-construal, which mirrors how one defines oneself in terms of one's relationship with others and relates to one's perceived happiness (Beckstein et al., in press).

While our article has limited space to elaborate each dyadic theory, the development of these recent nursing frameworks suggests a clear shift from the patient-centered to a dyadic view that encapsulates both the patient and the care partner. All models reviewed emphasize the shared appraisals of illness and coping behaviors from both the patient and the care partner. The harmonizing appraisals and coping strategies are important for dyadic adjustment as well as dyadic health. However, the process is also influenced by cultural, gender, and marital factors; the illness condition and its developmental stages should also be considered. Practically, constructs in these models are malleable as different diseases may need different illness management and coping strategies. Some key elements are mentioned conceptually but not incorporated as a component in the model. For example, while satisfying the needs of both the patient and the care partner is deemed important (Lyons & Lee, 2018), the Theory of Dyadic Illness Management does not specify the position of dyadic needs in the model. Thus, elucidating and standardization of measures and research design remain an open question (Helgeson et al., 2018). Nonetheless, these insightful dyadic models in nursing research field provide numerous avenues for future studies, yet their methodological applications are still limited.

Using Dyadic Data in Nursing

Using dyadic analysis is relatively nascent in nursing research, although such analyses could reveal the complex but important information in illness management processes. Here, we compare two major benefits that interdependent analyses offer: 1) values through multiple informants (i.e., both the patient and care partner) and 2) abilities to capture dynamic interpersonal processes with both correlational and longitudinal designs. While some research questions can be also examined using individual data, interdependent data analysis may better address interpersonal influences on appraisals and behaviors regarding illness management.

Multiple Informants

Most behavior theories recognize the effect of influential others (e.g., peers, parents). Driven by the individual-level perspective, the normative influence is often operationalized as one's perceived approval of performing a health behavior (e.g., does your partner approve your smoking?). In contrast, research using interdependent data utilizes data from both informants in a dyad. For example, by assessing both smoking status and relationship quality among young couples, researchers found that couples' relationship quality can be negatively influenced by discordant patterns of smoking during pregnancy (Cornelius et al., 2017). It would be difficult to address such research question solely using a single-informant perspective.

Interpersonal Dynamics

Although a longitudinal design does not exclusively belong to dyadic modeling, it can capture unique interactions between behavioral change and interpersonal relationship with the consideration of time. One study using dyadic latent panel analysis captured the change in spousal similarity over time and how this changing variable impacted on depressive symptoms (Desai et al., 2012). The extension from an individualistic level to a dyadic level enables the identification of variable change at a family level. An obvious drawback of dyadic longitudinal design is the difficult implementation and potential attrition. For instance, one of the common difficulties that researchers often face is the varying patterns based on maternal and paternal report with higher participation rates among mothers (Atkins, 2005).

Empirical and Theoretical Considerations when Using Interdependent Data

Interdependent data are also known as nested data or clustered data. These terms suggest that individuals are embedded within their social, cultural or environmental systems (Atkins, 2005). Conventional statistical methods such as ordinary least square (OLS) regression analysis are unsuitable due to the violation of independence (Heck & Thomas, 2015). Conducting these analyses with the statistical assumption of independence could lead to biased results such as loss in the degrees of freedom, biased standard errors, and incorrect *p*-values (Kenny, 1995). Instead, structural equation modeling (SEM; e.g., Kim et al., 2018; Segrin et al., 2005) and multilevel modeling (MLM; e.g., Leineweber et al., 2014; Lyons & Sayer, 2005a) are commonly used for dyadic analyses in health and family research fields.

The structure of interdependency of data should be considered in several aspects. While it seems rather reasonable to assume dependencies among couples or members of a family, it is, for instance, not so when it comes to *yoked linkages* (i.e., people might not even be familiar with each other but share similarities such as environmental experiences and stimuli) (Kenny et al., 2006). To facilitate such decisions, the Intra-Class Correlation (ICC) can be utilized as an empirical estimate of interdependency (Robson & Pevalin, 2015). The theoretical range of an ICC is between 0 and 1, with 0 meaning no evidence of multilevel structure in the data and 1 meaning that the multilevel structure explains 100% of variance in the data. While an ICC value of .10 is sufficient to argue for the MLM structure (Lee, 2000), it is also strongly recommended to focus on the given structure of the data rather than solely on the ICC cutoff value (Nezlek, 2008). However, ICC values are also useful in capturing the variability in a cluster on a scale. For example, in a doctor-patient communication study, the comparisons of ICC values showed that the communicative ability of a physician was perceived quite differently by his/her patients, whereas physicians scored their patients quite similarly on their communication skills (Kenny et al., 2010).

As most multilevel methods are based on non-dyadic contexts, the ICC values should be interpreted with cautions. Rather than simply relying on these indices for interdependencies, researchers should examine the theoretical meaning when applying statistical analyses to a sample—including the research context (e.g., spouses, parents and children, doctors and their patients), the research question (e.g., similarities/differences between the dyads), as well as the inherent nature of the variables under investigation (e.g., coping behaviors, communication skills, quality of relationships).

Once having determined the structure of given data from both an empirical and a theoretical perspective, researchers also need to carefully examine the type of dyads in the data (Card et al., 2008). For example, dyads can be categorized by how distinguishable they are (Gonzalez & Griffin, 2012; Kenny et al., 2006). *Distinguishable* dyads refer to dyads that can be differentiated based on heterogeneous manifestations in a meaningful grouping variable such as gender (e.g. heterosexual partners) or role (e.g. doctor, patient), while *indistinguishable* dyads, also often referred to as *exchangeable*, share the same characteristics of a certain variable (e.g. same-sex partners) (Kenny et al., 2006; Ledermann & Kenny, 2017). Testing the indistinguishability is thus far limited to conceptual and theoretical levels. Kenny et al.'s (2010) study, nevertheless, shows that ICC values could be used to compare the variability in each role and the large difference indicates their distinguishability (i.e., communicative skills were perceived quite differently from each other). Some studies also used simple t-test to estimate the couple-member/sex differences (e.g., Van Vleet et al., 2018). It is of note that, for indistinguishable dyads, less parameters are estimated than for distinguishable dyads, which results in more statistical power to determine significant effects (Ledermann & Kenny, 2017).

Models That are Usually Used in Dyadic Analysis

Kenny et al. (2006) proposed three models that are of high importance in the analysis of dyadic data: The Actor-Partner Independence Model [APIM; (Kenny & Cook, 1999); Figure 1], the Common Fate Model [CFM; (Kenny & La Voie, 1984); Figure 2], and the Mutual Influence Model [MIM; (Kenny, 1996); Figure 3]. In all figures, we have adapted these models in a family nursing scenario where a couple—the husband (the patient) and the wife (the care partner)—are managing the dyadic illness together. Following the Theory of Dyadic Illness Management (Lyons & Lee, 2018), the dyadic appraisal of symptoms and care values (i.e., illness appraisal) and how the couple manage illness (i.e., management behavior) are two key elements in the family nursing process. These models could well encapsulate common situations in health research areas, and advanced models could also be developed based on these models.

Actor-Partner Independence Model (APIM)

The APIM is one of the most frequently used models in couple research (Ledermann & Kenny, 2012). With this model, the so-called actor (intrapersonal) and partner (interpersonal) effects can be examined simultaneously. Figure 1 illustrates a general outline of an APIM, which has been widely used in cross-sectional (Cook & Kenny, 2005) and longitudinal research designs (Kenny & Kashy, 2011). As the APIM diagram shows, both dyads' illness appraisal has an impact on their own management behavior as well as their partner's behavior. Accordingly, researchers used the APIM to investigate dyadic relationships between social support and mental health of patients and their partners in the waiting period for coronary artery bypass grafting, finding that the patient's social support influences their own and their partner's mental health quality (Thomson et al., 2012). Similarly, Varner et al. (2019) applied the APIM to examine longitudinal associations between illness uncertainty and relationship quality in couples with one partner undergoing prostate cancer treatment. Results underscored the relevance of relationship processes in context of diseases, as illness uncertainty persisting over time negatively impacted supportive behaviors in both the partner and the patient, resulting in lower levels of relationship satisfaction and poorer health outcomes on the couple level. These result highlight the benefits of considering intrapersonal as well as interpersonal information, thereby providing more nuanced patterns of how individual and couple processes unfold (Thomson et al., 2012).

Common Fate Model (CFM)

Contrary to the APIM framework, where it is assumed that one partner's predictor variable directly influences the other partner's outcome, the CFM assumes that there is a latent variable (also known as a "level-two" or "between-person" variable) which affects members of a dyad simultaneously (Figure 2). In the example of Figure 2, we see that both illness appraisal and management behavior are treated as latent variables in the CFM. This latent variable can either be an internal factor resulting from a dyad's relationship (e.g., relationship satisfaction) or an external source (e.g., the neighborhood disorder or community support) (Maroufizadeh et al., 2018) As a crucial characteristic of the CFM, this latent variable is assumed to work at a dyadic level and not an individual level, meaning that the focus is placed on shared experiences among dyads. Marital satisfaction between a couple and genetic influences between parent and child can be conceptualized as latent common variables (Maroufizadeh et al., 2018). For instance, Ledermann et al. (2010) used a CFM to model shared couple experiences, such as relationship stress, communication patterns and relationship quality, finding that both couple's communications and relationship stress influence the relationship quality on a dyad level.

While the CFM is highly appreciated for its better comprehension of dyad's constructs, it has been insufficiently applied in longitudinal or cross-sectional research (Ledermann & Kenny, 2012). Notably, the CFM seems unsuitable for most dyadic datasets and few valuable research questions were raised based on the CFM (Kenny, 2018).

Mutual Influence Model (MIM)

The MIM assumes that two outcome variables of a dyad share a bidirectional causation (Kashy et al., 2006). As Figure 3 shows, the couple's management behavior is not only the outcome of their dyadic illness appraisal, but their management behavior also has a reciprocal relationship. For instance, one partner's level of perceived stress, resulting from a given stressful event, does not only affect his/her own level of overall relationship satisfaction but is also assumed to exert an influence beyond the individual level (Randall & Bodenmann, 2009). Previous research has highlighted the negative reciprocal nature of relationships satisfaction among spouses (Ramos Salazar, 2015), supporting the idea of mutual influence (as the name of the model already indicates) among both partner's relationship satisfaction. As to its applicability in practice, the MIM is, like the CFM, commonly used in cross-sectional designs but tends to be under-utilized.

One tricky issue about the MIM is the reciprocal relationship (also known as non-recursive relationship or feedback loop) between the outcome variables because this linkage may cause model stability problem (Acock, 2013; Kline, 2016). A practical consequence is that model identification of the non-recursive model can fail; remedies for such a case include fixing some paths to zero and adding an exogenous variable (Kline, 2016).

Extended APIM Models

These three models mentioned above serve as fundamental frameworks in dyadic analysis. Researchers can modify the models based on the research questions. Figure 4, for example, illustrates an extended APIM which includes two mediators (i.e., marital satisfaction perceived by the couple); in this way, researchers could examine the roles of other variables in the dyadic illness management process (for more details for this model, see Ledermann et al., 2011). For instance, by extending the APIM, researchers used co-parenting relationship quality (i.e., perceived working alliance between parental persons) as a mediator, highlighting the important role of co-parenting for adolescents (Coates et al., 2019). In another study investigating couples struggling with infertility, Casu et al. (2018) applied an extended APIM to test for the indirect effect of infertility-related stress in women and men on associations between spirituality and reported quality of life. Results emphasized the potential of spirituality as a shared coping mechanism, helping couples seeking infertility treatment to maintain their quality of life.

Another extension of the APIM is the actor–partner interdependence moderation model (APIMoM; Garcia et al., 2015). In a study conducted by Van Vleet et al. (2018), the APIMoM was used to analyze data from dyads with one partner recently being diagnosed with type 2 diabetes. Adding gender as a moderator enabled the authors to investigate whether the influence of communal coping strategies on diabetes problem solving was different for men and women. Apart from the examples in health research field, more discussions on the extensions of the APIM can be found in Garcia et al. (2015).

It is worth noting that the above APIM-based model family mainly follows the work by Kenny et al. (2006). Analytic interests in dyads existed in family research for a long time. From simple methods (e.g., mean scores, difference scores between each dyad), to repeated measures analysis of variance, to MLM, another lineage of dyadic models is found (Sayer & Klute, 2005). Limited to the length and introductory aim of this article, the advantages of MLM over those conventional methods cannot be fully covered. It is, however, important to remember that these dyadic multilevel models could examine incongruence between each dyad (Lyons & Sayer, 2005a, 2005b; Sayer & Klute, 2005).

Longitudinal Dyadic Models

Most applications of dyadic modeling are based on cross-sectional data, while peer-reviewed methodological guides for dyadic application in longitudinal designs tend to be neglected (Foran & Kliem, 2015) except for a few in the more recent literature in nursing (Lyons & Lee, 2020). Dyadic latent growth curve modeling is frequently used for longitudinal interdependent data analysis. As illustrated in Figure 5, when we plan to investigate the complex relationships between illness appraisal and management behavior in couples with a longitudinal perspective (this view is especially highlighted in chronic illness management; Berg & Upchurch, 2007), such latent growth curve models could usefully capture how the dyad's illness appraisal predicts the management behavior of their own and their partner in the beginning (intercept) and in a long run (slope). Researchers have utilized this model to investigate the long-term relationship between emotional behaviors and physical health symptoms (Haase et al., 2016). Some recent applications using the dyadic latent growth curve models also considered heterogeneities in the sample. For example, based on couples' conflict resolution strategies across time, it is possible to extract couple groups that used qualitatively different strategies (Li et al., 2019).

Related Statistical Issues

Most statistical packages are able to implement dyadic modeling as the base of this modeling is MLM and SEM. Researchers have compared statistical software for MLM and SEM in the multilevel context (Tabachnick & Fidell, 2019), as well as for dyadic modeling specifically (Ledermann & Kenny, 2017). For a practical guideline, Table 1 provides several references with syntax examples by which readers can compose their own syntax according to the software used. Several technical issues are elaborated below.

MLM vs. SEM Approaches

Both MLM and SEM have been used for dyadic analyses. While the SEM approach can provide a wide range of fit statistics thus enabling researchers to assess how well the applied model fits the data, the MLM approach can deal with small sample size and has often been preferred over the SEM method given its more straightforward implementation (Ledermann & Kenny, 2017). Moreover, statistical analysis of indistinguishable dyads compared to distinguishable dyads within an APIM framework appears to be more complex using SEM, as it for instance demands adjustments of model fit statistics and the restriction of parameters (for further details of the use of SEM for interchangeable dyads, see Olsen and Kenny (2006)). Given the pros and cons of these two approaches, Multilevel SEM (MSEM) has been introduced to incorporate features of MLM and SEM (Preacher et al., 2010). MSEM also provides the foundation of several methods such as multilevel mediation (Preacher et al., 2010), the CFM (Ledermann & Kenny, 2012) and dyadic Growth Curve Modeling (Ledermann & Macho, 2014). Within MSEM, structural equation models can be established on each level of interdependent data, thereby allowing for latent constructs at an individual as well as group level (Mehta & Neale, 2005; Silva et al., 2019).

Dyadic Covariance and Change over Time

Few methodologists consider how to select which variables are most appropriate for dyadic analysis. Some couple-level variables such as household income can vary if they are assessed separately, but theoretically the number reported by a dyad should be highly similar. There are also data from a couple that may even show no overlap (e.g., employment status or job type among certain age groups); dyadic modeling in such case is problematic as the common influence is empirically nonexistent.

Furthermore, researchers should consider the theoretical model with special attention to theories of change and how this may explain how the scores from each partner relate over time (i.e., within dyad correlations at each time point and how change in one member of the dyad predicts change in the other over time). If the impact of couple conflict on physiological stress responses, mood, or smoking behaviors happens and in the moment with different effects for actors versus partners, dynamic dyadic research designs that capture the momentary and daily changes are needed (e.g., Du & Wang, 2016). It may also be the case that the covariance between a couple on a health indicator (e.g., similarity in body weight index or alcohol consumption) changes with couples becoming more similar in health indicators over time and change in one partner predicting change in the other (e.g., Cobb et al., 2015). It can also be the case that dyads fluctuate in a synchronized way in the moment or on a daily basis (Azhari et al., 2020; Ferrer & Helm, 2013; Ferrer & Nesselroade, 2003; Pauly et al., 2021). Hypotheses regarding the theory for dyadic changes need to be carefully detailed to fit the analytical approach best.

Sample Size

Specific sample size calculation for dyadic models still needs future investigation. However, the minimal sample size in dyadic analyses mainly depends on ICC and missing data as well as expected effect sizes (Du & Wang, 2016). As recommended, at least 50 dyads are needed to perform reliable dyadic data analyses based on the MLM if there are no missing data from any dyads; if there are singletons (e.g., only the mother provided the answer but not the father), this minimal sample size should be larger (Du & Wang, 2016). Researchers may also consider some general guidelines for sample size calculation for MLM and SEM (Hox et al., 2018; Hoyle, 1995).

Missing Data

Missing data issues are particularly challenging in dyadic data analyses since a dyad has more than one case. As other types of analyses, the portion of singletons could affect the estimation (Dong & Peng, 2013). Commonly used statistical techniques including Full information maximum-likelihood (FIML), Multiple Imputation (MI), and Expectation-maximization method (EM) are often applied to handle missing data when the data are missing at random. While there are some novel statistical approaches to treat missing data when they are dyadic nonignorable (Ahn et al., 2019), unfortunately, statistical software packages that are often used in social science cannot perform these approaches.

Advanced Models

We should note that growth curve modeling (Planalp et al., 2017), cross-lagged panel modelling (Kuiper & Ryan, 2018), and machine learning technologies such as decision trees (Hush & Porter, 2010) have been applied to dyadic data. These new applications enable researchers to address more complex research questions. However, these complex models with longitudinal designs also face a number of concerns including the minimal sample size, number of variables, and robust theoretical frameworks (Foran & Kliem, 2015). To capture a more ecological health behavior perspective, researchers also need to utilize a larger and representative sample. Specific guidelines on these practices are not established yet.

It is also important to extend the nature of modeling beyond the dyad. Although triadic modeling and network analysis are not new (Kenny et al., 2006), applications beyond dyads are limited in practice especially in health and nursing research fields. Take network analysis for example. This statistic has recently become a popular method as it can capture the intercorrelations among a large number of variables (Hevey, 2018). However, most studies using network analysis are focusing on intrapersonal variables (e.g., cognition, physical illness).

Discussion

In this article, we briefly reviewed the limitations of an individualistic approach and how a dyadic perspective can enrich research in nursing and other health research fields. Previous research based on dyadic models has extended nursing theories to dyadic processes and provided a possible empirical vehicle to consider the interdependencies that are vital for care practices (Berg & Upchurch, 2007; Helgeson et al., 2018; Lyons & Lee, 2018). This article provided an introduction of dyadic modeling for nursing research that we hope will be useful to encourage more researchers to consider these methods in their research agenda.

Since interpersonal relationships exist widely across cultures, we believe the dyadic modeling has a considerable global generalizability. However, cross-cultural validation of the dyadic interpersonal relationship should be of concern. As discussed by Li and Huang (2010), the differential mode between interpersonal dyads in Chinese society is distinctively different from the organizational mode in the West, whereby the neutral and independent perceptions regarding each other in the Western interpersonal context may not be the same in China. This interpersonal difference has potential impacts on health behaviors. For example, refusing a cigarette offer is uneasy for Chinese adolescents especially when it is offered by a person with seniority, and parents or friends of parents sometimes may encourage adolescents to smoke (Zhao et al., 2018). Given this cultural difference in interpersonal relationships, future research may include variables that reflect one's perception about the interpersonal hierarchy or order (e.g., using a moderator in the APIM).

Another related issue is about the measurement (although this perennial problem is not limited to dyadic modeling). For people who tend to express their feelings in an indirect way and avoid emotional expressions, typical instruments using "strongly agree/disagree" may be inappropriate especially given the interpersonal orders (e.g., respect from son to mother, or from citizen to king) (Tsai, 2019). The indirect way of expressions may require the use of other measurement techniques that are more sensitive to interpersonal dynamics. It may require a rescaling and testing of some measures, such as using an item-count approach instead of a regular Likert scale (Tsai, 2019).

In sum, the dyadic framework is appropriate for nursing research and theory, but continues to be under-utilized. With increasing established health psychological models having been extended with a dyadic framework, more fine-grained analyses of environmental processes and interpersonal relationships are possible. While dyadic models are promising, some methodological issues (e.g., cross-cultural suitability, nonignorable missing data) still deserve more investigations.

Compliance with ethical standards conflict of interest

The authors declare that they have no conflict of interest.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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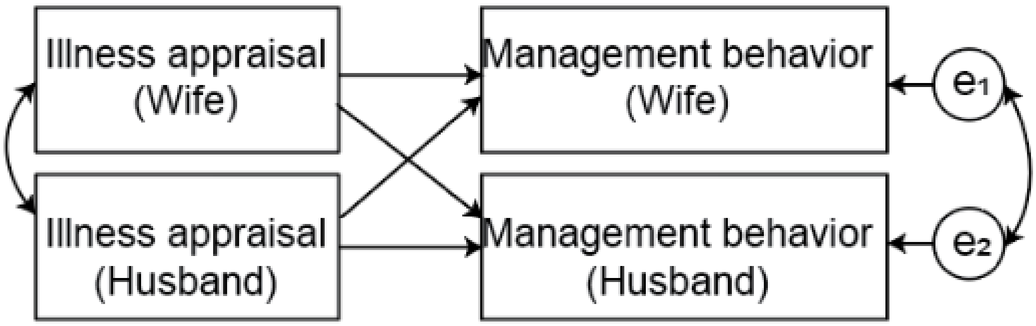
Table 1

Common Statistical Package Selections for Dyadic Modeling

Program	Notes
IBM SPSS	The classical book on dyadic modeling by Kenny et al. (2006) covers numerous syntax and datasets with well-illustrated examples. Readers who use IBM SPSS, SAS, MLwiN can easily find these files from the book's website. If you are new to dyadic modeling, this is an important reference.
Stata	Readers may also like the straightforward MLM syntax structure in Stata. Preciado et al. (2016) provide a helpful tutorial for dyadic logistic multilevel models using the xtmelogit command. If readers prefer a jargon-free style and would like to learn/review some basic implementations of MLM in Stata, Robson and Pevalin (2015) provide a user-friendly textbook. With the tutorial of logistic MLM, readers can also read a book by Liu (2016) and construct dyadic models based on non-normal distributed data.
Mplus	For Mplus users, although the Mplus user's guide (Muthén & Muthén, 1998-2017) does not directly include examples about dyadic models, user-friendly tutorials can be found (Wickham & Macia, 2018; Wickrama et al., 2016). As Mplus is a powerful software for latent variable analysis, readers can find advanced extensions of dyadic models such as a hybrid model combining the APIM and CFM (Wickham & Macia, 2018). Using latent variables also enables researchers to consider more complex measurement models (Geiser, 2021). Advanced readers could construct dyadic models based on textbooks on growth mixture modeling (Wickrama et al., 2016) and multilevel SEM (Silva et al., 2019).
R	R users can find abundant guidelines for dyadic model programing (Knight & Humphrey, 2019) including complex designs such as longitudinal APIM (Gistelinck & Loeys, 2019). Based on R, some online programs for dyadic data analysis (e.g., DyadR) have also been developed.

Figure 1

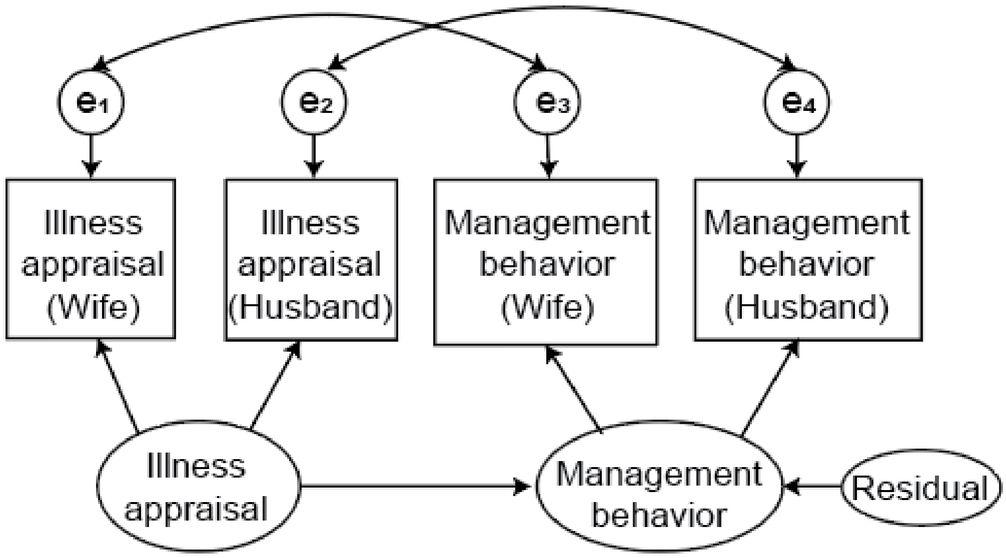
Actor-Partner Interdependence Model (APIM) in Dyadic Illness Management



Note. The residual is showed with a circled e. The dashed line in (b) shows an indirect effect.

Figure 2

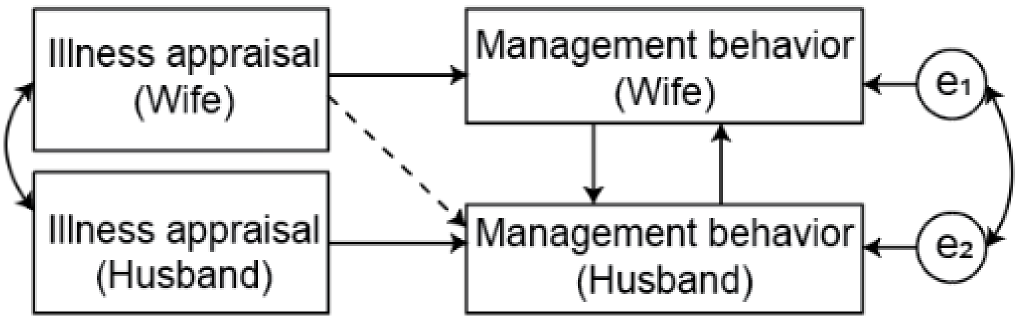
Common Fate Model (CFM) in A Dyadic Illness Management



Note. The residual is showed with a circled e. The residual of the endogenous variable (i.e., management behavior) is showed in a different way.

Figure 3

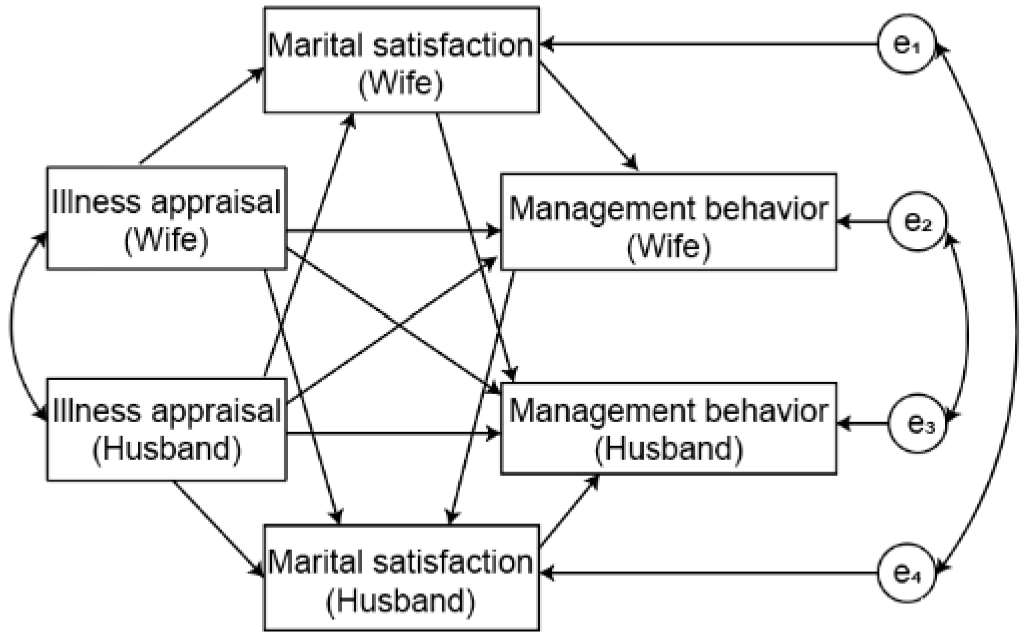
Mutual Influence Model (MIM) in A Dyadic Illness Management



Note. The residual is showed with a circled e. The dashed line reflects an indirect effect.

Figure 4

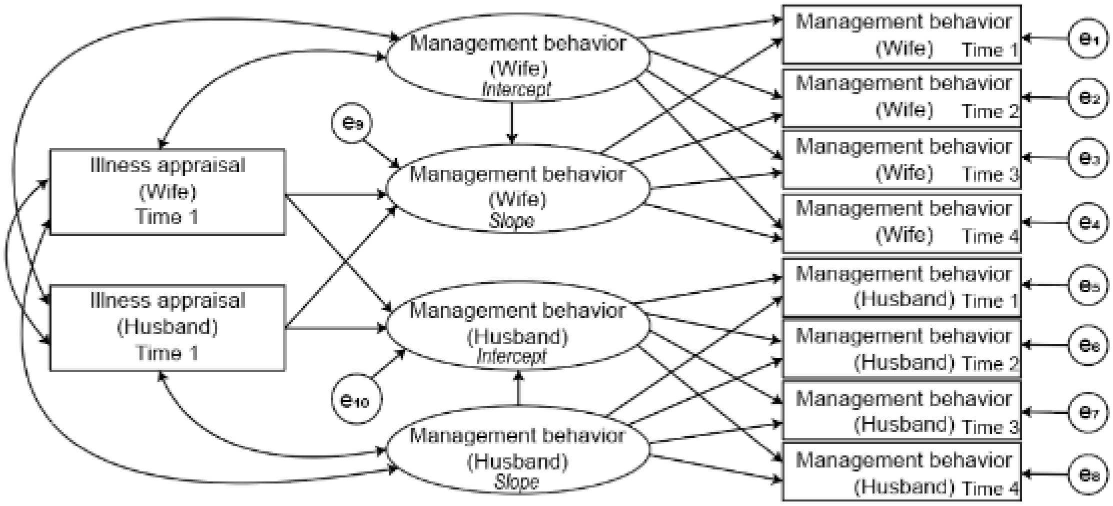
Actor-Partner Mediation Interdependence Model in A Dyadic Illness Management



Note. The residual is showed with a circled e.

Figure 5

Dyadic Latent Growth Curve Model in A Dyadic Illness Management



Note. The residual is showed with a round with e.