Best Practices for Multiple Imputation in the Context of the Actor-Partner Interdependence Model

Candidacy Examination

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Abstract

Dyadic data analysis refers to statistical approaches used on paired individuals to understand how one individual's characteristics influence the other's outcomes. One dyadic framework is the Actor-Partner Interdependence Model (APIM), where the effects from two members within a dyad are used to directly model their own and the other's outcomes. While a growing body of research has investigated the APIM, little research has been conducted on how to best address missing data in a dyadic context.

The primary goal of the present study was to investigate five different forms of missing data treatments on an APIM: listwise deletion, full information maximum likelihood, and three variations of multiple imputation, a technique that handles missing data by generating several plausible values based on observed data. Secondary goals included the investigation of listwise deletion versus multiple imputation in a multivariate linear regression model and the review of past research on dyadic analysis in developmental and clinical psychology with emphasis on parental depression, coparenting, and child emotion dysregulation.

Monte Carlo simulations were used to generate data with self-imposed missingness, using parameters from the Future of Families and Child Wellbeing Study. Gold standard approaches like passive multiple imputation were used during the imputation procedure. However, final models demonstrated negligible differences regarding standard errors and significant effects. Additionally, no notable differences were found in study variables between multiply imputed datasets. The present study concludes with a summary of current research and suggestions for future research for both missing data analysis and family systems research.

Introduction

Dyadic Data Analysis

Definition

A "dyad" refers to a pair – mother and father, student and teacher, therapist and client, identical twins – and is regarded as "the fundamental unit of interpersonal interaction and interpersonal relations" (Kenny et al., 2006, p. 1). Panko and Kinney (1992) define a dyad as a "a pair relationship that functions as a recognizable organizational unit for a significant period of time" (p. 244). Dyads can be distinguishable or indistinguishable. In a sample of heterosexual couples or teacher-child dyads, dyad members can be identified by a distinctive and meaningful variable, such as gender or role. Indistinguishable dyads include same-sex couples and identical twins; even if members in a dyad may be able to be distinguishable (e.g., being born first or second in a set of twins), this variable is likely meaningless in the context of an APIM.

A data frame is one of the most common ways of storing data for analysis (Hadley Wickham, 2019). A data frame is a rectangular spreadsheet consisting of *rows* (observations) and *columns* (variables; Ismay & Kim, 2019) with every value belonging to a unique combination of row and column (Wickham, 2014). In a traditional "wide" data frame, each column is a variable and each row is a participant, often beginning with an identifier variable to distinguish participants from one another. In research where repeated measures are collected from participants, a data frames may be structured hierarchically, often called "nested" or "molten", where one column now contains concatenated data values that were previously distributed among multiple columns (Wickham, 2014).

A dyadic data frame is a unique type of hierarchical data structure where individuals (dyad members) are nested within groups (dyads; McMahon et al., 2006). There are two types of dyadic data structures – wide and pairwise. A wide data structure is like most traditional data frames where each dyad has one row with separate columns for each member's variables. A pairwise data structure (also called double entry data structure) combines elements of individual and hierarchical structures so each row contains observations for a member of the dyad and the member's partner.

Techniques

The Actor-Partner Interdependence Model (APIM) is a model of dyadic (two-person) relationships and has become a popular statistical approach when data is collected from both members of a dyad (e.g., mother and father, teacher and student, a pair of twins). In an APIM on mother-father dyads, the effect of father's variable X on father's variable Y is called an actor effect, while the effect of father's variable X on mother's variable Y is called a partner effect. A basic APIM can capture four paths: two actor effects and two partner effects (Cook & Kenny, 2005; Kenny, 2018). Dyadic data analysis with indistinguishable dyads is historically more difficult than with distinguishable dyads although both are possible[1] (Kenny et al., 2006). There are other forms of the APIM, such as APIMs with mediation or moderation (where the mediator or moderator may be between-dyads or mixed/within-dyads; Garcia et al., 2015), longitudinal APIMs (Gistelinck & Loeys, 2019), or group APIMs (where members are nested within dyads and dyads are further nested within groups; Bonito, 2022).

When conducting an APIM, there are two gold standard statistical frameworks: multilevel modelling (MLM) and structural equation modeling (SEM; Kenny et al., 2006). MLM refers to analysis conducted on hierarchical or nested data (e.g., students in a classroom) that violates the assumption of non-independence (Peugh, 2010). SEM refers to a set of techniques used to

[1] Please note that this proposal will exclusively focus on a basic APIM: two partner effects, two actor effects, in dyads with a distinguishing characteristic.

analyze the associations between directly observed variables and latent variables (unobserved variables derived from other interrelated observed variables (Beran & Violato, 2010). Both frameworks are commonly used with APIMs and generally produce similar results (Hong & Kim, 2019). However, the main difference between MLM and SEM is its data structure. Unlike most MLMs, MLM APIMs require manipulating the data into a pairwise data structure (Kenny et al., 2006). However, a SEM APIM can be conducted with a traditional wide data structure.[2]

Below is the equation for a basic APIM using a SEM framework. In a SEM framework, the APIM is defined by two structural equations, one for each dyad member (Garcia et al., 2015). The equation for Person 1 (e.g., father) is

$$Y_1 = b_0 + a_1X_1 + p_1X_2 + e_1,$$

while the equation for Person 2 (e.g., mother) is,

$$Y_2 = b_1 + p_2X_1 + a_2X_2 + e_2,$$

with a_1 and a_2 designating actor effects and p_1 and p_2 designating partner effects. Both predictor variables (X_1 and X_2) are used to predict both outcome variables (Y_1 and Y_2); the estimated paths include those from X_1 to Y_1 (actor effects), the paths from X_2 to Y_2 (actor effects), the paths from X_2 to Y_1 (partner effects), and the paths from X_1 to Y_2 (partner effects). In a SEM framework, to test differences in actor and partner effects (e.g., is the effect of social support on marital quality different across mothers and fathers?), the two actor paths and the two partner paths are constrained and differences are detected by testing for any significant changes in model fit (Lawrence et al., 2008). Because APIMs with distinguishable dyads are saturated (also called just-identified), the model has zero degrees of freedom (*df*) and chi-square is equal to zero (Cook & Kenny, 2005; Kenny & Ledermann, 2010).

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[2] For the purposes of this proposal, I will focus exclusively on the SEM approach with a wide data structure.

Other than the APIM, dyadic data analysis also includes the Common Fate Model (CFM), the Mutual Influence Model (MIM), and the Social Relations Model (SRM). In a CFM, the two members do not influence each but are influenced by the same external variables (Kenny & la Voie, 1985). A MIM is similar to an APIM, but instead of examining partner effects, both members' outcomes predict each other's outcomes (Cook, 1998; Kenny, 1996). A SRM is unique as it can be used on groups of people (e.g., a family; mother, father, older daughter, younger son), with distinguishable or indistinguishable members, and differs from the APIM as models actor effects, partner effects, and *relationship effects*, which is the effect of an actor on a partner after the actor and partner effects have been removed (Cook & Dreyer, 1984; Kenny & La Voie, 1984). Additional forms of dyadic study include round-robin, checkerboard, and block designs (Kenny & La Voie, 1984), group iterative multiple model estimation (GIMME; Gates & Liu, 2016), and Bayesian approaches (e.g., bilinear mixed-effects models, shared-parameter models; Ahn et al., 2019; Hoff, 2005), but these are outside the scope of the present study.

Dyadic Data in Clinical/Developmental Contexts

Clinical Applications of Dyadic Data Analysis

Clinical research is no stranger to dyadic data analysis, both quantitative (Whittaker et al., 2022) and qualitative (Collaço et al., 2021). In clinical psychology, APIMs have been primarily used as a tool to examine constructs like therapeutic alliance and session outcome (e.g., Kivlighan et al., 2014; Li et al., 2021; Zilcha-Mano et al., 2016). To the best of my knowledge, Kivlighan (2007) was the first to utilize an APIM to model the effect of perceived therapeutic alliance on session quality for both therapists and clients. Before Kivlighan (2007), Cook (1998) used an early version of the APIM to study husband-wife behavior over time in marital counselling. Dyadic data analysis can also be found in clinical trials, including husband-wife marital counselling during chemotherapy (Lewis et al., 2019) and different-sex parent dyads transitioning to into parenthood where one parent had been diagnosed with PTSD (Fredman et al., 2017).

Family Systems and Coparenting

Family systems theory is a theory of human behavior and emotional functioning that conceptualizes the family as an "emotional unit" (p. 38) and accounts for how the interlocking relationships among family members impact how each family member thinks, feels, and behaves (Kerr & Bowen, 1988). Like the nested nature found in some dyadic data structures, families also are hierarchical in structure; specifically, a hierarchically organized system consisting of smaller subsystems (e.g., husband-wife, brother-sister), embedded in a larger systems (e.g., community, nation; Cox & Paley, 1997). These smaller subsystems are characterized by boundaries and rules on how to repeatedly interact within and across family subsystems (Cox & Paley, 1997) and both can affect and be affected by other family subsystems, regardless of their place in the overall family hierarchy (Belsky et al., 1996).

One highly researched subsystem is the parent subsystem. Parenting is characterized by the enculturation, socialization, and preparation of children to survive and thrive in expected situations and environments (Bornstein, 1991; Committee on Supporting the Parents of Young Children et al., 2016). According to Belsky's model of parenting (1984), three domains determine parenting quality and experience – the parents' psychological resources, child characteristics, and contextual sources of stress and support. The coparenting relationship falls under this third contextual domain. Coparenting refers to the ways parents or parental figures collaborate, share responsibilities, and coordinate or fail to coordinate in the act of childrearing, separate from the marital, sexual, and legal aspects of the parental relationship (Feinberg, 2002, 2003). Therefore, in many families, the spousal and parent subsystems consist of the same individuals but should be recognized as separate subsystems, with the parenting and coparenting relationships also separate from each other.

Coparenting differs from parenting as the act of parenting is inherently dyadic, occurring between a parent and a child, while coparenting encompasses a triadic relationship between two parents and a child (McHale, 1995). According to Feinberg (2003), a high-quality coparenting relationship consists of : 1) the joint management of family interactions (e.g., prevention of the children “taking sides” during parental conflict), 2) supporting each other as coparents, 3) agreement on family goals and childrearing values, and 4) an equitable division of child-related labor. Coparenting may fluctuate from day-to-day, as several fluid factors like parental stress, parental negative mood, and father work hours can impact coparenting quality (McDaniel et al., 2018). A recent systematic review found that coparenting was related to improved relationship quality, parenting satisfaction, and family functioning (Campbell, 2022).

Dyadic data analysis is uniquely suited to study constructs within a family system. By examining both actor and partner effects, researchers can analyze the differences between how mothers and father perceive the coparenting relationship. Fagan and Palkovitz (2019) studied perceptions of coparenting and child engagement in different-sex dyads and found that when fathers reported higher levels of perceived child engagement, mothers reported lower coparenting support over time. However, in a sample of new parents, Le and colleagues (2016) found longitudinal actor and partner effects for both men and women’s relationship quality, but not coparenting quality.

Research on different-sex parents suggests that family relations unequally impact mothers and fathers. According to the father vulnerability hypothesis, fathering and father-child relationships are more vulnerable to familial discord compared to mothering and mother-child relationships (Goeke-Morey & Cummings, 2007). Relative to mothering, fathering can specifically impact child development through three pathways: 1) the relationship between marital quality and fathering, 2) the child's exposure to paternal expressions of relationship discord, and 3) the relationship between relationship quality and paternal psychological functioning (e.g., depression). However, these associations can be bidirectional, as in turn, fathering itself can be improved or hindered by constructs like maternal gatekeeping, relationship satisfiaction, and negative child temperament (see Wang et al., 2020 for a review). Dyadic data analyses and APIMs have been used to investigate the father vulnerability hypothesis and how fathers can be uniquely impacted by familial or parenting-related stressors.

Previous dyadic research has demonstrated interparental differences regarding family constructs. In a Chinese sample, men high in neuroticism were more likely to report a lower-quality coparenting relationship with their wives, specifically reporting higher conflict, reprimanding, and disparagement, but women high in neuroticism only reported higher coparenting conflict (Jiang et al., 2021). In a sample of African-American different-sex dyads, Sutton and colleagues (2017) found that mothers' and fathers' psychological distress significantly predicted both their own and their partner's negative couple interactions (i.e., low warmth, high hostility). However, in a study involving a mother-father interaction task, the mother's negative behaviors were predictive of poor maternal and paternal parenting, while the father's negative behaviors were only predictive of poor paternal parenting, demonstrating the unique effect of maternal behavior on fathers (Sutton et al., 2017). Ponnet (2014) found a significant negative actor effect of financial stress on positive parenting practices in fathers, but not mothers. Despite prior support, not all studies that utilized APIMs found supportive evidence for the father vulnerability hypothesis (Ponnet et al., 2013; Stevenson et al., 2019), prompting the need for further research.

Parental Depression and Child Emotion Regulation

Emotion regulation refers to the processes of monitoring, evaluating, and modifying emotional reactions (Thompson, 1991). As its opposite, emotion *dys*regulation refers to patterns of emotional experiences, expressions, and reactions that disrupt goal-directed activity (Thompson, 2019) or as more commonly seen in children, an intolerance of negative emotional experiences and an inability to regulate behavior during those experiences (Dvir et al., 2014). Emotion dysregulation is transdiagnostic (Berking & Wupperman, 2012; Paulus et al., 2021) and can manifest in several behaviors, including irritability, outbursts, and inattentiveness (Stringaris & Goodman, 2009; Tonacci et al., 2019). In children, the prevalence of emotion dysregulation varies by age and gender, with younger age and being male decreasing the likelihood of utilizing emotion regulation strategies (Sanchis-Sanchis et al., 2020).

In 2009, 15 million children were estimated to be currently living with a parent with major or severe depression (National Research Council and Institute of Medicine, 2009). Unfortunately, depression in both mothers and fathers is associated with a variety of adverse child outcomes (Doyle et al., 2022; Hanington et al., 2012). According to Belsky's (1984) model of parenting, the parents' "personal psychological resources" are "the most influential determinant of parenting" (p. 91). Depression negatively effects social interactions through interpersonal processes (e.g., excessive reassurance seeking, negative feedback seeking; Hames et al., 2013) and has been shown to negatively impact the coparenting relationship (Tissot et al., 2017). Similarly, Takeishi and colleagues (2021) found that higher-quality coparenting at three-months postpartum was associated with lower maternal depressive symptoms. It is important to recognize that parental depression exists within a family system and thus impacts and is impacted by other family processes. For example, Vakrat and colleagues (2018) demonstrated that high sensitivity, low intrusiveness, and high child engagement in fathers reduced the negative effect of maternal depression on family cohesion.

Barriers to Dyadic Data Analysis

The main barrier to conducting dyadic data analysis is the recruitment of matched pairs. Dyadic data collection is inherently more difficult to conduct compared to traditional individual-based studies due to the sheer increase in participants. In developmental research, fathers are historically difficult to recruit (Davison et al., 2017). Systematic reviews and research on research participation have repeatedly demonstrated the lack of paternal representation in family or child research (Davison et al., 2016, 2018; Miller & Feudtner, 2016; Parent et al., 2017; Phares et al., 2005). Due to increases in academic interest in the role of fatherhood (e.g., Coley, 2001), increasing paternal research participation has become a salient issue.

Researchers have documented potential reasons behind paternal underrepresentation. While both mothers and fathers are driven to participate in research due to a desire to contribute to science, fathers are uniquely motivated by a desire to increase paternal representation, while mothers are more driven by curiosity (Yaremych & Persky, 2022). Clinical trial research has demonstrated several lessons on how to successfully recruit and retain whole families, including valuing family time, developing professional relationships with participants, and building trust (Andrews & Davies, 2022; Huntington et al., 2017). In particular, fathers and families of color can be difficult to recruit and retain, leading to underrepresentation in research (Costigan & Cox, 2001; Passmore et al., 2022), but community partnerships and well-trained personnel may increase recruitment efforts (Julion et al., 2018).

Missing Data Analysis

Definition

Missing data is a pervasive problem in quantitative research in the fields of education (Peng et al., 2007), medicine (Little et al., 2012), and psychology (Enders, 2003). Efforts to "solve" the issue of missing data have been well-documented for decades (Rubin, 1976). When addressing missing data, it is critical to understand the mechanisms behind the missingness and the structure of the data (e.g., individual, hierarchical). Missingness is defined by the absence of meaning, as missing data are unobserved values that would be meaningful if included in analysis (Little & Rubin, 2020).

Since missingness can be driven by different kinds of mechanisms, it is important distinguish between different patterns of missingness. According to Rubin (1976), missingness can be described using three categories: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). When data are MCAR, the probability that a data point is missing is the same for all data points and any mechanisms or causes that drive missingness are unrelated to the data or participants. When the probability that a datapoint is missing is the same for all values *in the same group*, then data are considered MAR. When the probability of a datapoint to be missing is unknown, then data are considered MNAR (van Buuren, 2021a).

It can be difficult to determine the underlying mechanism driving missingness. Determining whether missingness is MCAR versus MAR is testable (Enders, 2010) via two strategies: 1) a series of univariate independent t-tests to compare subgroups of missing data, or 2) a t-test-like approach applied to the entire dataset to evaluate mean differences on every variable (Little, 1988), although this global approach is not sensitive to potential auxiliary variable that correlate with the missingness. Regardless, neither of these approaches are widely used and Little and Rubin argue that operating under the MAR assumption, rather than the MCAR assumption, is more “natural” and leads better prediction of missing values (2020, p. 23). Unfortunately, determining whether missingness is MNAR versus MAR is not possible since the information needed for such a test is missing (van Buuren, 2021).

Techniques

There are multiple ways to address missing data, including deletion and insertion. Listwise deletion is the removal of participants (rows) where *any* data is missing, while pairwise deletion only removes information when data from certain variables are missing (e.g., the dependent variable; Nguyen, 2022). Techniques that fall under the umbrella of “single imputation” involve replacing a missing value with a single value. Mean imputation is the replacement of missing values with the mean of the variable (column) average. Person-mean imputation is the replacement of missing values with the mean of a row for a subset of variables. Specifically, if an item on a questionnaire is missing and the available items are averaged together to account for the missing item, this is called a prorated score (Mazza et al., 2015). Regression imputation is the use of a regression model to predict the missing value by using other variables present. A version of this called stochastic regression imputation adds a randomly selected residuals to the regression model to reflect uncertainty in the predicted value (Little & Rubin, 2020). Hot-deck imputation replaces missing values with available data from a “similar” participant (Andridge & Little, 2010) and cold-deck imputation replaces missing values from an external source, like a previously-collected dataset (Schlomer et al., 2010). In cases of poor retention, longitudinal analysis often substitute the most recently-collected value for any missing values, referred to as last observation carried forward (LOCF; Lachin, 2016). While single imputation methods are simple and easy to accomplish, these methods infamously introduce bias (Zhang, 2016).

Multiple Imputation

Definition

Multiple imputation is a powerful tool to address missing data (Enders, 2017) and improves upon single imputation by replacing missing values several times, generating several plausible values based on the how variables are distributed in the dataset as well as the relationships among variables (Li et al., 2015), which produces a list of multiple different generated datasets (Heymans & Eekhout, 2019). Instead of averaging these multiply generated datasets together into a single dataset, analysis is conducted on every single dataset and then results are pooled together into a final estimate plus standard error using specific pooling rules called “Rubin’s rules” (Rubin, 1987; see van Buuren, 2021a, chapter 9 for review). When using multiply imputed data, it is important that the models to impute the data and the models to analyze the data do not differ (Schafer, 2003).

In multiple imputation, predictor matrices are used to delineate which variables should be used to predict specific target variables (Zhang, 2016). In a predictor matrix, a “1” in a cell indicates that the column variable is used to predict the row variable; a “0” indicates that the column variable is not used to predict the row variable. A predictor matrix requires that each variable with missing values be assigned an imputation method. In the commonly used R package *mice* (van Buuren, 2022), the default imputation method is predictive mean matching (PMM), where missing values are replaced by randomly selecting a value from a small set of donors that have predicted values closest to the predicted value of the missing entry (van Buuren, 2021). PMM is a robust method as PMM can be used for continuous, categorical, or binary data.

Other robust methods include weighted PMM (“Midas touch”), random sampling from observed values, classification and regression trees, and random forest imputation (van Buuren, 2021).

A popular form of multiple imputation is multiple imputation by chained equations (MICE). The MICE procedure is well described by Azur and colleagues (2011); the steps have been briefly summarized below. First, a simple imputation (e.g., mean imputation) is performed for every missing value in the dataset to act as a “placeholder”. Second, the “placeholder” imputations for a single selected variable are set back as missing. Third, all or some of the other variables in the dataset are used as independent variables to predict the observed values in the selected variable. Fourth, the missing values for the selected variable are replaced with the predicted values from the regression model. Finally, the second, third, and fourth steps are repeated for every variable with missing data; each repetition is called an iteration. These steps are repeated for a specified number of times, with the imputations being updated after each iteration.

Multiple Imputation and Questionnaire Data

Over the years, there have been several modifications and improvements to the already-advanced technique of multiple imputation, specifically when using questionnaire data. One approach is the “just another variable” (JAV) approach, where each questionnaire item and the scale score are imputed separately (White et al., 2011). JAV may lead to problems as the sum of the imputed items may differ from the imputed scale score (von Hippel, 2009). An arguably better option is passive multiple imputation, where the computation of the scale score occurs as part of the imputation procedure and is built inside the predictor matrix (Heymans & Eekhout, 2019). Prior research has demonstrated passive imputation showing smaller bias and more precision compared to JAV-like approaches (Eekhout et al., 2018) and is regarded as a best practice for multiple imputation (Woods, Davis-Kean, Halvorson, King, Logan, Xu, Gerasimova, et al., 2021), although some researchers have warned against passive multiple imputation's exclusion of scale scores in the imputation model (Mainzer et al., 2021). More advanced research may use Bayesian approaches like substantive model compatible fully conditional specification (SMCFCS; Bartlett et al., 2015).[3]

Missing Data in Clinical/Developmental and Dyadic Contexts

Effects of Missing Data

Considering the history of clinical trials and retention issues (e.g., Vancampfort et al., 2021), there is ample research regarding missing data treatments on clinical data. Little and colleagues (2012) emphasized the need for methodological measures, rather than purely analytic approach, to prevent missing data in clinical trials, including increasing the flexibility of treatment regimens, shorter follow-up periods, purposeful add-on study designs, and the addition of rescue medications to treatment regimens. While missingness in clinical trials inevitably leads to bias (Groenwold & Dekkers, 2020), treatment of missing data does not significantly differ than other forms of data collection. Multiple imputation is a well-recommended treatment for missing clinical data (Austin et al., 2021; Jakobsen et al., 2017), although other methods such as full information maximum likelihood (FIML) is common among clinical trials (Staudt et al., 2022). Clinical trials also often use LOCF, although this method is known for its biased results (Lachin, 2016; Mavridis et al., 2019).

Specific to dyadic data analysis, Warner, Kenny, and Stoto (1979) were the first to name the "missing partner" effect, which exists when a partner is missing in a dyad. Cases where a partner may be "missing" include longitudinal large-scale studies of families where divorce,

[3] For the purposes of this proposal, I will focus on the passive multiple imputation approach and the predictive mean matching (PMM) method for continuous data.

incarceration, or other events may lead to one partner no longer participating in data collection (Brown, 2014). Unfortunately, studies on the missing partner effect are few and focused on analyses other than APIM, including a round-robin design (Warner et al., 1979), SRM (Cook & Dreyer, 1984), and linear regression (Young & Johnson, 2013). To the best of my knowledge, the missing partner effect has not been specifically examined in the context of an APIM. Unfortunately, examination of the missing partner effect is outside the scope of the present study.

Barriers to Multiple Imputation

In an extensive review of best practices, Woods and colleagues (2021) identified six barriers to multiple imputation: 1) unfamiliar with statistical software, 2) lack of training, 3) pressure to use simpler methods for quick turnaround, 4) lack of confidence in accuracy of final outcome or ethical concerns, 5) added complexity to analysis, and 6) lack of guidelines. Unfortunately, many of these barriers can only be accomplished by more widespread training, dissemination of good practices, and debunking of misconceptions (e.g., that multiple imputation is "making up" data; van Ginkel et al., 2020). Additionally, current software is not as user-friendly as possible considering the potential error messages that may occur (e.g., model non-convergence; Nguyen et al., 2021; Rombach et al., 2018).

Difficulty in understanding or conducting multiple imputation has led to its avoidance or misuse. The following studies all utilized APIMs and a form of arguably flawed missing data treatment. Kim and Kim (2022) conducted extensive analyses on multivariate dyadic data but described their imputation procedure in fewer than three sentences; while Kim and Kim (2022) mentioned that PMM was utilized as their method, they did not describe if any predictor matrix had been specified. For an APIM of friendship dyads, Popp and colleagues (2008) conducted multiple imputation with an expectation-maximization algorimth for missing data, but ultimately utilized single imputation “instead of multiple imputations to simplify the data analyses” (p. 1031). Lam (2020) utilized “multiple imputation then deletion” (MID) on a dataset of partnered dyads; MID is a technique where all missing data is multiply imputed by any rows with missing dependent variables are ultimately removed (von Hippel, 2007), an approach that is negligibly less efficient than regular multiple imputation in most cases but can produce biased parameters if any auxiliary variables are associated with patterns of missingness (Sullivan et al., 2015). Williams and Cheadle (2016) conducted a unique “hybrid” version of multiple imputation and FIML, where non-imputed datasets were utilized in analytic models; to the best of my knowledge, I have never seen this technique used in other papers or recommended by other experts. In conclusion, the misuse of multiple imputation with dyadic data and the lack of specification of predictor matrices highlights a lack of consensus for good practices when handling both dyadic and missing data.

The Present Study

Prior research has been conducted on applying multiple imputation to MLMs (Grund et al., 2018) and SEMs (Lee & Shi, 2021). However, to the best of my knowledge, this area of research has exclusively focused on analysis where conducting an APIM was not the end goal. The purpose of this candidacy project is to investigate multiple imputation methods with the end goal of conducting an APIM because there is a lack of research on missing data treatments, specifically multiple imputation, for dyadic data structures and APIMs. Additionally, there is no gold standard or recommended practices for addressing missing data specifically for dyadic data structures or APIMs outside of general recommendations like multiple imputation or FIML (if using a SEM framework).

The present study aimed to examine, document, and evaluate multiple imputation methods specifically in the context of an APIM. First, I investigated five different forms of missing data treatments on an APIM: listwise deletion, FIML, and three variations of multiple imputation. Second, I examined listwise deletion versus multiple imputation in a multivariate linear regression model. Finally, I reviewed past studies on dyadic analysis in developmental and clinical psychology research, specifically focusing on depression, emotion regulation, and coparenting.

Method

Sample

I used data from the Future of Families and Child Wellbeing Study (formerly known as the Fragile Families and Child Wellbeing Study; FFCWS), a longitudinal study of nearly 5000 children born in large U.S. cities between 1998 and 2000 to primarily unmarried mothers (Reichman et al., 2001). Data were collected from mothers, fathers, and children across seven timepoints to answer research questions on family and child functioning, particularly concerning the role of fatherhood (Brown, 2014; McLanahan et al., 1998). The present study only conducted analyses cross-sectionally when the target child was approximately five years old (Bendheim-Thoman Center for Research on Child Wellbeing, 2019). Previous research has utilized FFCWS to study coparenting (Fagan & Palkovitz, 2019; Rinelli, 2009), parental depression (Turney, 2012), and child emotion dysregulation (Doom et al., 2022). FFCWS public data was accessed through Princeton University's Office of Population Research (https://pop.princeton.edu/research/data-archive). After data cleaning procedures were applied (see below), the final sample size was 4292 families. In the final sample, most parents identified as non-Hispanic Black (mothers 48.8%, fathers 50.4%). At the time of childbirth, the mean parent age was 26 years old (*M* = 26.51, *SD* = 6.60) with 18.7% of mothers and 10.6% of fathers at or below the poverty line. At the time of childbirth, only 10.3% of parents had a college or graduate degree.

Measures

Parental depression. Mothers' and fathers' depression were assessed using the Major Depressive Episode questions from the Composite International Diagnostic Interview – Short Form (CIDI-SF; Kessler et al., 1998), a 15-item self-report measure that assessed the presence or absence of depressive symptoms on a yes/no scale. The CIDI is a standardized assessment and assesses symptoms consistent with the DSM-IV criteria for Major Depressive Disorder including changes in weight, trouble sleeping, and loss of interest. Participants were asked if within the past year if he or she had experienced a depressive episode lasting two weeks or more. If the participant answered no, the CIDI-SF was not administered, and participants were given a CIDI-SF score of zero. If the participant answered yes, participants completed the 15 CIDI-SF items. CIDI-SF was summed as a measure of depression severity, a procedure previously conducted on similar depression data (e.g., Rottenberg et al., 2019). Please note that only six items were included in the scale score (see Table 1 for all items) with one item used to determine whether the participation was administered the CIDI-SF. Greater CIDI-SF sum scores indicate greater depression severity.

Coparenting support. Coparenting was assessed with a scale specifically created for FFCWS. Mothers and fathers completed a 6-item measure to assess perceptions of coparenting support (e.g., "How often do you and partner discuss problems that come up raising child?") on a Likert scale from 1 (*always*) to 4 (*never*). All coparenting items were reverse scored so higher scores indicated greater coparenting quality. See Table 1 for all items.

Child emotion dysregulation. Child emotion dysregulation was assessed by the primary caregiver using the Child Behavior Checklist (CBCL; Achenbach, 1992). The CBCL is a 113-item measure that assesses problem behaviors on a 3-point Likert scale from 0 (*Not true*), 1 (*Somewhat or sometimes true*), and 2 (*Very true or often true*). Please note that Year 5 of FFCWS only administered a subset of CBCL items (72 original CBCL items). Emotion dysregulation was measured by summing the Anxiety/Depression, Attention Problems, and Aggressive Behavior subscales (Masi et al., 2021). Unfortunately, the CBCL was only completed by the target child's primary caregiver, not both mothers and fathers. The primary caregiver was selected based on who the target child primarily lived with. Across the sample, primary caregivers included mothers, fathers, siblings, grandparents, other family members, and family friends. However, the vast majority of primary caregivers were biological mothers (97.8% of families who participated in Year 5 data collection; Bendheim-Thoman Center for Research on Child Wellbeing, 2019, p. 76).

Data Analysis

Data Cleaning

Code, summary statistics, and model summaries are available online in a public repository, not including raw or simulated data (Calabrese, 2023). Data analysis was conducted in R and RStudio (v 4.2.2; R Core Team, 2013). First, the FFCWS dataset was loaded into RStudio for data cleaning purposes. Data was filtered to only include relevant demographic and study variables for each parent: age, race, poverty level, and education status. Variables were renamed and values were recoded as non-applicable when appropriate (e.g., negative values; see Bendheim-Thoman Center for Research on Child Wellbeing, 2019, p. 20 for missing data codes). Families were excluded if they did not participate in Year 5 data collection ($N = 606$). After exclusion criteria was applied, specified variables were reverse-coded (as described earlier), and subscales scores were calculated. If some items of a questionnaire were missing, prorated scores were used instead as the scale score. The final sample size was 4292 families.

Data Generation and Multiple Imputation

Two data generation models were written separately, an APIM and a linear regression model. Models were estimated using *lavaan::sem()* with no missing data treatment specified using the *lavaan* package (Rosseel, 2012). The APIM used in the present study was based on Garcia's (2018) *lavaan* syntax, which allows for both actor and partner effects, as well as intercepts, variances, error variances, and covariances for each dyad member. The *lavaan* syntax was written with distinguishable dyads to distinguish between effects of mothers and fathers, although please note that models with distinguishable dyads cannot be used to generate interpretable model fit indices as $df = 0$ (Kenny, 2020). Linear regression was a multiple linear regression model with two predictors and no interaction effect.

Predictor matrices were created as described in Heymans and Eekhout (2019). For the APIM, three matrices were created: 1) a liberal predictor matrix with a passive multiple imputation approach where maternal and paternal data are used to predict maternal and paternal missing values (i.e., actor and partner effects), 2) a conservative predictor matrix with a passive multiple imputation approach where only maternal data was used to predict maternal missing values and only paternal data was used to predict paternal missing values (i.e., only actor effects), and 3) an unspecified predictor matrix for comparison purposes. For the linear regressions with emotion dysregulation, two predictor matrices were created: 1) a predictor matrix with passive imputation and 2) an unspecified predictor matrix for comparison purposes.

Readers may ask why child emotion dysregulation was not included in the first data generation procedure. If I had included child emotion dysregulation in the first data generation procedure, then all relevant variables (parental depression, coparenting, and emotion dysregulation) would have been found in one multiply imputed dataset. While this would make imputation and analyses simpler, I did not do this because the data generation model and the imputation model should resemble the final analysis model as closely as possible (Jiang, 2014; Schafer, 2003). Since the present study focuses on two forms of analysis (APIM and linear regression), then two separate data generation and imputation procedures had to be conducted. Therefore, due to the different data generation models and the randomness inherent in the imputation procedure, the parental depression scores would likely be different between the two analyses.

A missingness template was created with *simsem::miss()* using a Monte Carlo approach with the *simsem* package (Pornprasertmanit et al., 2021). Under the MAR assumption, 15% missingness was specified as the multiple imputation approach utilized 15 imputation, as Dong and Peng (2013) recommends that the number of imputations should always be the same or greater than the percentage of missing values. Three datasets per data generation model were created of different sizes: small ($N = 200$), medium ($N = 500$), and large ($N = 2000$), similar to work conducted by Jiang (2014), with the missingness template imposed on each dataset during generation. Copies of these "raw" simulated datasets were saved before imputation for comparison purposes. Between saving copies of the simulated data and conducting multiple imputation, values for the scale scores were made missing so the passive multiple procedure would overwrite the scale scores to avoid the pitfalls of the JAV approach (White et al., 2011). This step is important so the average of all items and the scale scores for respective items would be identical. Finally, multiple imputation was conducted on all generated datasets using the *mice* package (van Buuren, 2022). Nine multiply imputed datasets (*mids* objects) were created for the APIM, and six multiply imputed datasets were created for the linear regression.

As recommended by Heymans and Eekhout (2019), multiple imputation was conducted using *mice::mice()* with 15 imputations and 30 iterations per imputation. For comparison purposes, the default predictor matrices were imputed using *mice::quickpred()*, which uses simple statistics to select predictor for missing values (van Buuren et al., 1999). Note that the multiply imputed datasets that utilized *quickpred()* skipped the step where the values of subscale totals were made missing, which means that the observed values utilized during the imputation procedure contained both scale scores and prorated scores (Mazza et al., 2015). PMM was used for continuous variables and polytomous logistic regression was used for unordered categorical demographic variables.

Structural Equation Modelling

After multiple imputation, the multiply imputed datasets were converted from *mids* objects to lists of data frames and analyzed according to the original SEM model specified during data generation with the *sem.mi()* function from the *semTools* package (Jorgensen et al., 2022). For comparison purposes, additional analyses were conducted on datasets that did not undergo multiple imputation in the style of Berry and Willoughby (2017). The APIM was conducted twice more with two different missing data treatments, listwise deletion and FIML. The linear regression was conducted once more with listwise deletion.

Fixed effects, variances, covariances, and fit statistics, as well as descriptive statistics and intercorrelations, were provided for each model and dataset. Model fit was assessed using the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and root mean square error of approximation (RMSEA; like used by Hong & Kim, 2019) with index recommendations by Hu and Bentler (1999; i.e., CFI ≥ .95, RMSEA ≤ .06; SRMR ≤ .08). However, please note that model fit indices are uninterpretable with saturated models (i.e., APIMs with distinguishable dyads; Kenny, 2020). Additionally, even if these model fit indices were interpretable, it is impossible to use these estimates for model comparison purposes due to each model being fitted to different values (Jorgensen, 2019). Further review of model fit indices is provided in the Discussion.

Results

Descriptive Statistics

Before proceeding, it is important to discuss that sometimes missing values may still be present in the multiply imputed dataset due to multicollinearity among variables, as the *mice()* function will fail to impute if the data contains extremely collinear variables (van Buuren, 2021a; see section 6.3). This issue is normally avoided by further specification of the predictor matrix, but since the predictor matrices are an important part of the present study's research question, altering the predictor matrices for the sake of avoiding this issue would defeat the goal of the present study. Therefore, I have also included how many missing values were present in the multiply imputed datasets alongside other descriptive statistics (see Tables 2–3). Since researchers cannot and should not assume that any given function will perfectly address all missingness, it is good practice to check the prevalence of missingness in multiply imputed data before data analysis. Additionally, it should be noted that some *df* values may have fractional estimates. This is due to the mice package using the Barnard-Rubin correction (Barnard & Rubin, 1999) for *df* estimation on pooled data (see Heymans & Eekhout, 2019, section 9.4; van Buuren, 2021a, section 2.3)

Means, standard deviations, minimums, maximums, standard errors, and prevalence of missing values are reported for relevant study variables in Tables 2–3. Univariate ANOVAs were conducted on relevant study variables to examine whether there were significant mean differences between predictor matrices or sample sizes, but no significant differences were found. Cronbach's alphas for each dataset can be found in Tables 4–5. Internal consistency for coparenting was consistently adequate ($RANGE_{FATHER}$ = .69 to .78, $RANGE_{MOTHER}$ = .75 to .81), even higher for depression ($RANGE_{FATHER}$ = .91 to .96, $RANGE_{MOTHER}$ = .93 to .95). For the emotion dysregulation data, coparenting ($RANGE_{FATHER}$ = .72 to .79, $RANGE_{MOTHER}$ = .76 to .81) and child emotion dysregulation ($RANGE_{CHILD}$ = .82 to .90) also had adequate internal consistency. Internal consistency was best for the large dataset (N = 2000) compared to the small or medium datasets.

APIM with Parental Depression

Listwise deletion. For the small model, there was a significant actor effect of paternal depression on paternal coparenting (β = -.48, SE = .17, p = .006). For the medium model, there was a significant actor effect of paternal depression on paternal coparenting (β = -.61, SE = .14, p < .001) and maternal depression on maternal coparenting (β = -.37, SE = .16, p = .020). For the large models, all actor and partner effects were significant at p < .001. For models of all sizes, CFI = 1, TLI = 1, RMSEA = 0, and SRMR = 0.

Full information maximum likelihood. For the small model, only the actor effect of paternal depression on paternal coparenting was significant (β = -.38, SE = .17, p = .024). For the medium model, there was a significant actor effect of paternal depression on paternal coparenting (β = -.65, SE = .14, p < .001) and maternal depression on maternal coparenting (β =

-.32, *SE* = .14, $p = .025$). For the large model, all actor and partner effects were significant at $p < .002$. For models of all sizes, CFI = 1, TLI = 1, and RMSEA = 0.

Multiple imputation with liberal predictor matrix. For the small model, only the actor effect of paternal depression on paternal coparenting was significant ($\beta = -.34$, *SE* = .15, $p = .024$) and this remained the only significant effect in the medium model ($\beta = -.46$, *SE* = .12, $p < .001$). Maternal depression did not significantly predict maternal coparenting in the medium model ($\beta = -.24$, *SE* = .13, $p = .069$). For the large model, all actor and partner effects were significant at $p < .008$. Estimates of model fit were expected for a saturated APIM for the small (TLI = 1.213, SRMR = .001), medium (TLI = 1.110, SRMR < .001), and large models (TLI = 1.044, SRMR < .001). For all models, CFI = 1 and RMSEA = 0.

Multiple imputation with conservative predictor matrix. For the small model, only the actor effect of paternal depression on paternal coparenting was significant ($\beta = -.40$, *SE* = .18, $p = .023$). For the medium model, there were significant actor effects of maternal depression on maternal coparenting ($\beta = -.32$, *SE* = .15, $p = .036$) and paternal depression on paternal coparenting ($\beta = -.59$, *SE* = .14, $p < .001$). For the large model, all actor and partner effects were significant at $p < .007$. Estimates of model fit were expected for a saturated APIM for the small (TLI = 1.259, SRMR = .001), medium (TLI = 1.134, SRMR < .001), and large models (TLI = 1.039, SRMR < .001). For all models, CFI = 1 and RMSEA = 0.

Multiple imputation with no specified predictor matrix. For the small model, no actor or partner effects reached the threshold for significance. For the medium model, only the actor effect of paternal depression on paternal coparenting was significant ($\beta = -.43$, *SE* = .14, $p = .002$) as maternal depression did not demonstrate a significant actor effect ($\beta = -.25$, *SE* = .16, $p = .102$). For the large model, all actor and partner effects were significant at $p < .039$.

Estimates of model fit were expected for a saturated APIM for the small (TLI = 1.259, SRMR = .001), medium (TLI = 1.259, SRMR = .001), and large models (TLI = 1.053, SRMR < .001). For all models, CFI = 1 and RMSEA = 0.

Linear Regression with Child Emotion Dysregulation

Listwise deletion. For the small model, neither maternal nor paternal coparenting had a significant effect on child emotion dysregulation (R^2 = .02, F(2, 118) = 1.12, p = .330, $R^2_{Adjusted}$ < .01). For the medium model, only maternal coparenting negatively predicted child emotion dysregulation (β = -.07, SE = .02, p < .001) although the model itself was still weak (R^2 = .06, F(2, 284) = 8.56, p < .001, $R^2_{Adjusted}$ = .05). For the large model, both maternal coparenting (β = -.07, SE = .01, p < .001) and now paternal coparenting (β = -.02, SE = .01, p = .047) were both negative predictors of child emotion dysregulation (R^2 = .05, F(2, 1152) = 28.81, p < .001, $R^2_{Adjusted}$ = .05).

Multiple imputation with specified predictor matrix. Neither maternal nor paternal coparenting had a significant effect on child emotion dysregulation in the small model (R^2 < .01). Maternal coparenting had a significant negative effect on child emotion dysregulation in the medium model (β = -.04, SE = .01, p = .014, R^2 = .02) and in the large model (β = -.04, SE < .01, p < .001, R^2 = .03).

Multiple imputation with no specified predictor matrix. Neither maternal nor paternal coparenting had a significant effect on child emotion dysregulation in the small model (R^2 < .01). Maternal coparenting had a significant negative effect on child emotion dysregulation in the medium model (β = -.04, SE = .01, p = .014, R^2 = .02) and in the large model (β = -.04, SE < .01, p < .001, R^2 = .02).

Review of Logged Events

The *mice* packages includes a feature called *logged events* that produces a list of any problems that arose during the imputation procedure (van Buuren, 2021a, section 9.1.5). As mentioned previously, multicollinearity may occur during the imputation procedure due to variables being too similar (Nguyen et al., 2021). Fortunately, the *mice* will automatically apply a ridge penalty to problematic variables to avoid multicollinearity (van Buuren, 2022). During the imputation procedure, there were some problems with multicollinearity. Across sample sizes and predictor matrices, only four variables caused issues during the imputation procedure (coparenting items #7 and #8 for both mothers and fathers) that caused *mice* to apply ridge penalties. There were no issues with multicollinearity with the child emotion dysregulation data. Additionally, there were no convergence errors during model construction.

Discussion

In the present study, I have reviewed past research on both dyadic and missing data analysis, specifically through a clinical and developmental context, and conducted dyadic data analysis (APIM) and multivariate linear regression on multiply imputed data while maintaining best practices. However, results revealed very little, if any, differences between models fit to different multiply imputed data regarding the APIM and the linear regression model. Below I discuss issues and limitations regarding model fit and comparison, as well as provide further review of past research on missing data analysis. Finally, I discuss the findings of the analyses alongside prior studies on parental depression, coparenting, and child emotion dysregulation. The present study demonstrated significant actor and partner effects of parental depression on coparenting, but depression in fathers appeared as a more persistent effect on coparenting than maternal depression. When predicting child emotion dysregulation, maternal coparenting was revealed as a significant predictor with little effect driven by paternal coparenting.

Issues with Model Fit and Comparison

The present study has highlighted issues when evaluating multiply imputed APIMs with distinguishable dyads. First, there is the issue of model comparison. As said by Dr. Terrence Jorgensen, statistics professor and creator of the *semTools* package, “You cannot compare models that are fitted to different data. Period.” (Jorgensen, 2019). Although no other data sources were used other than FFCWS, I only used FFCWS data to generate parameters and simulate new data of various sample sizes. Further, I assigned those simulated datasets a specific predictor matrix to create several multiply imputed datasets, each with its own imputed values. At no point did the model for the APIM or the linear regression change; only the datasets changed. Therefore, any estimates of model fit cannot be used to compare models.

Related to this point is the issue of model fit when dyads are distinguishable. As described previously, an APIM with distinguishable dyads is a *saturated* model with zero *df* and chi-square equal to zero (Cook & Kenny, 2005, p. 107; Kenny & Ledermann, 2010). Because both of these values are zero, RMSEA is set to zero, CFI is always one, and TLI is always equal to or greater than one (Kenny, 2020). Additionally, other pooled model fit estimates like AIC and BIC are currently not able to be computed with multiply imputed structural equation models (objects of class *lavaan.mi*; Gullickson, 2022), although these estimates still could not be used for model comparison since each model is fit to a different multiply imputed dataset. Despite the dyads being distinguishable by parent gender, one option would be to run the APIM as indistinguishable, which would have set the actor effects, partner effects, variances, intercepts, and error variances as equal for both members in the dyad (Garcia, 2018). This strategy would have properly generated model fit estimates like CFI, TLI, and AIC, but any differences in depression or coparenting between mothers and fathers would be unobservable. Additionally, all models would still be fitted to different data, making model comparison impossible.

Review of Missing Data Treatments

With the inability to directly compare model fit in mind, I will still discuss the models and multiply imputed datasets alongside past research on missing data analysis. First, models fit to large datasets and estimates generated from large datasets consistently fared better than models fit to small datasets. Internal consistency among items was greater in larger datasets. In both the APIMs and linear regression models, the models fit to large datasets had a greater number of significant effects (α = .05) and beta estimates grew larger as sample size increased.

The only differences between APIMs were observed in models fit to small and medium datasets. First, the only model fitted to a small dataset that contained no significant effects was based on data imputed with the unspecified predictor matrix, specifically the "quick" predictor matrix that was first described by van Buuren and colleagues (1999). Second, models fitted to medium datasets that did not contain significant actor effects of maternal depression were based on data imputed with the liberal and unspecified predictor matrices. All APIMs based on large datasets demonstrated all significant actor and partner effects. It is unclear what drove the significant effects in the liberal and unspecified matrices. However, the liberal and unspecified matrices notably differed from the conservative matrix, as the liberal and unspecified matrices utilized paternal data to predict maternal data, while the conservative matrix only used maternal data to predict maternal data and vice versa. Therefore, it possible that the additional variables in the imputation model afforded improved accuracy during the data generation procedure. Additionally, for the child emotion dysregulation models, no models based on small datasets contained any significant effects and all models based on medium datasets contained a significant negative effect of maternal coparenting on child emotion dysregulation. Paternal coparenting only barely reached the threshold for significance in the large model fitted to non-imputed data.

Prior and ongoing research is debating the advantages and disadvantages of various missing data treatments. The present study appears to support the theory that missing data treatments based on maximum likelihood methods versus multiple imputation methods are equivalent (Collins et al., 2001; Graham et al., 2007). Methods based on maximum likelihood methods typically have smaller standard errors compared to multiple imputation (due to the multiple imputation procedure involving randomness; Dong & Peng, 2013), but this was not observed in the present study. However, not all past research has endorsed multiple imputation as the gold standard, as other studies have found that methods like FIML (Xiao & Bulut, 2020) and complete case analysis (Hughes et al., 2019) performed equal to or better than multiple imputation. Additionally, using a time-intensive procedure like multiple imputation may not be necessary as long as sample size is sufficiently large (e.g., $N > 999$; Chang et al., 2020; Stavseth et al., 2019; Woods, Davis-Kean, Halvorson, King, Logan, Xu, Bainter, et al., 2021). To the best of my knowledge, only one simulation study has cautioned against passive multiple imputation (specifically exclusion of the scale score from the imputation model; Mainzer et al., 2021), but this study notably differed from other simulate studies due to its longitudinality and size (2000 simulated datasets with 1000 participants each). In future research, researchers should investigate how well passive multiple imputation procedures perform at larger sample sizes in both cross-sectional and longitudinal datasets.

Parental Depression

The present study highlighted how the effect of depression on coparenting differed by parent gender, which can be seen by how the actor and partner effects reached the threshold of significance in datasets of different sample sizes. As sample size increased, so did the number of effects that reached significance, but the actor effect of paternal depression reached the threshold of significance in almost every model, even at the smallest sample size. The present study is in line with prior research on depression and coparenting (Sutton et al., 2017; Tissot et al., 2016; Williams, 2018), but since the actor effect of paternal depression was more persistent than the effect of maternal depression, these findings also suggest that spillover effect of depression affects fathers' coparenting more than mothers, consistent with the father vulnerability hypothesis (Goeke-Morey & Cummings, 2007). Despite these, both actor and partner effects were significant predictors at the largest sample size, underlining the strong effect of depression on coparenting, regardless of parent gender.

The harmful effects of depression are multiplied when more than one parent is depressed. Parental depression is a predictor of child behavior problems, with maternal depression a moderator of paternal depression (Psychogiou et al., 2017) and paternal depression a moderator of maternal depression (Mezulis et al., 2004). The effect of an additional depressed parent may also vary by timing, as Gutierrez-Galve and colleagues (2019) found that paternal depression is associated with the risk of their child developing depression, mediated by maternal depression during the postpartum period. While the present study did not conduct moderation or mediation analysis, the presence of partner effects emphasized the interdependent nature of family functioning and is consistent with prior research. Finally, despite the present study's findings regarding paternal depression, a systematic review has identified that maternal depression is a notably stronger environment risk factor for offspring depression, relative to paternal depression (Natsuaki et al., 2014).

Prior research has also demonstrated that depression may negatively impact parenting. Coyne and Thompson (2011) reported that in a sample of mothers with preschool-aged children, depressed mothers were more likely to report avoidance of distressing thoughts and experiences and feeling “out of control” in their parenting role. Additionally, a meta-analysis found that depressed fathers demonstrate decreased positive parenting behaviors (e.g., warmth, acceptance, child involvement) and increased negative parenting behaviors (e.g., hostility, rejection, criticism; Wilson & Durbin, 2010). A longitudinal study showed how depression was associated with greater parenting stress and lower parent-child relationship quality, particularly in fathers (Fentz et al., 2021).

However, the present study focused on how parental depression directly impacted coparenting, not child outcomes or parenting ability. Studies have documented the negative effect of parental depression on coparenting. In a longitudinal study, Tissot and colleagues (2017) found that symptoms of parental depression were more likely to drive low coparenting support and higher coparenting conflict, rather than the reverse. Similarly, in a sample of mother-father dyads, psychological distress demonstrated actor and partner effects, negatively predicting negative couple interactions during an interaction task (Sutton et al., 2017). In a study of fathers and infants, depressed fathers were more likely to report lower coparenting relationship quality, which in turn was associated with lower father-child bonding and negative parenting behaviors (e.g., anger, rejection; Wells & Jeon, 2023). Outside of the coparenting relationship, paternal depression has been associated with lower relationship satisfaction, confidence, and affection, even when controlling for maternal depression (Ramchandani et al., 2011).

Research similar to the present study has already been conducted in the FFCWS sample, such as identifying significant associations among coparenting, relationship quality, and parental well-being (Rinelli, 2009). Using longitudinal APIMs, Fagan and Palkovitz (2019) found that coparenting support is specifically critical during infancy and early childhood, as coparenting support predicted improved perceived father engagement over time in both parents with significant actor and partner effects. To the best of my knowledge, Williams (2018) has conducted the most similar analysis to the present study with FFCWS participants. Using a longitudinal APIM framework, Williams (2018) used parental depression to predict coparenting quality longitudinally across the first five years of the child's life. Unlike the present study, Williams (2018) only found one partner effect of paternal depression on maternal coparenting between the third and fifth years of the child's life; despite this, results demonstrated strong actor effects across all waves.

However, not all prior research has found similar associations between paternal depression and coparenting as found in the present study. In a daily diary study, negative parental mood was associated with greater fluctuations in coparenting relationship quality, both in mothers and fathers (McDaniel et al., 2018). Yu and Xiao (2021) identified parental depression as a negative predictor of coparenting but did not test or report any differences between mothers and fathers. In a triadic interaction task, Tissot and colleagues (2016) found that maternal depression impaired the quality of mother-father coparenting support during an interaction task, but paternal depression did not exhibit a similar effect. Additionally, depression in either parent was not associated with coparenting conflict. In a follow-up analysis with the same sample, Tissot and colleagues (2017) again reported that depression in mothers was more likely to negatively affect the coparenting relationship compared in depression in fathers, although effects were found in both parents. However, differences in these studies and the present study may be due to how Tissot and colleagues (2016, 2017) utilized a dyad-level measure of coparenting (i.e., coparenting support and conflict scores were the same for mothers and fathers within the same dyad), while the present study considered self-reports of coparenting from both the mother and the father.

Considering mixed prior research, other unmeasured constructs may have impacted the association between parental depression and coparenting, such as marital or relationship quality. McDaniel and colleagues (2018) identified that parents who support each other as a relationship, not just as coparents, were more likely to have a high functioning coparenting relationship. Coparenting also often mediates or moderates other family processes, such as marital satisfaction and parenting behavior (Pedro et al., 2012), emotion regulation and parenting self-efficacy (Calabrese, 2022), and work-life conflict and parental depression (Zou et al., 2022).

The present study also utilized a unique sample characterized by vulnerability and low socioeconomic status (Reichman et al., 2001), so discrepancies with past research may be partially impacted by differences in sample characteristics. Previous but limited research has identified associations between coparenting and perceived financial distress (Stanford et al., 2022). In a longitudinal study of low-income families across fifteen months, depression did not predict coparenting and financial distress was not associated with depression or coparenting, but maternal depression significantly predicted maternal and paternal destructive conflict, which in turn was negatively associated with coparenting quality (Curran et al., 2021).

Child Emotion Dysregulation

In the present study, maternal coparenting had a strong negative effect on child emotion dysregulation. As mothers perceived a stronger coparenting relationship with their partner, child emotion dysregulation decreased. The effect of maternal coparenting was observed with every type of missing data analysis treatment, while the effect of paternal coparenting only barely reached significance in one model that utilized listwise deletion. These results suggest that maternal coparenting may be a stronger predictor of child emotion dysregulation compared to paternal coparenting.

It is important to note that the present study conducted cross-sectional analyses when the child was five years old. Early childhood is a critical time for children's socioemotional development due to influences from the parent-child relationship, friendships with peers, and new experiences and transitions (Ladd, 1999; National Research Council, 2000; Paley & Hajal, 2022). In the context of child development, coregulation refers to how parents work together and provide external regulation or scaffolding to facilitate the child's socioemotional and regulatory development and is strongly related to the coparenting relationship (Paley & Hajal, 2022). Coregulation has been associated with improved child socioemotional and self-regulation development during early childhood, further improved when parent-child interactions are positive in content (Lobo & Lunkenheimer, 2020).

Since the parent-child relationship and effective coregulation are important factors in shaping child socioemotional development, parental depression and lack of interparental coordination have been associated with psychological maladjustment in early childhood (Paley & Hajal, 2022). Depressed parents may have difficulty with maintaining positive parent-child interactions (Dietz et al., 2008), which can contribute to the worsening of child behavioral problems (Lunkenheimer et al., 2021). Additionally, parental depression is a strong risk factor of offspring depression (Olfson et al., 2003), particularly if the parent experienced childhood-onset depression (Silk et al., 2006). Parental depression specifically increases the risk that their offspring will utilize maladaptive emotion regulation strategies (e.g., passively waiting, emotional suppression, rumination), putting them at higher risk of psychopathology (Loechner et al., 2020; Silk et al., 2006). A large amount of prior research has demonstrated associations between parental depression and child emotion dysregulation (e.g., Crespo et al., 2017; Hoffman et al., 2006; van der Waerden et al., 2015).

Parental depression may impact child emotion dysregulation through the tripartite model, which argues that parents facilitate their child's socioemotional ability through observation and modelling, parenting practices, and the emotional climate of the family, including specific parenting style (Morris et al., 2007). Through this model, parents can facilitate the development of adaptive emotion regulation strategies in their children through modelling and parenting practices (Gunzenhauser et al., 2014), but parents with depression may be unable to adequately model emotion regulation skills to their children (Garber et al., 1991; Seddon et al., 2020). Depression may impair parents' ability to deliver developmentally appropriate childcare (Priel et al., 2020) and increase the risk of child emotion dysregulation through unsupportive emotion socialization practices (Seddon et al., 2020). In a longitudinal study of school-aged children, Carrère and Bowie (2012) found differences between mothers and fathers; paternal hostile emotion dysregulation predicted child externalizing behavior, although maternal hostile emotion dysregulation did not have a similar effect.

While a notable body amount of research has documented the associations among parental depression, coparenting, and child outcomes, few outcomes explicitly used coparenting as a predictor of child emotion dysregulation. To the best of my knowledge, the only study to directly model this was conducted by Tissot and colleagues (2016), who found that lower coparenting support predicted greater child externalizing and behavioral problems. Thomassin and colleagues (2017) conducted a similar analysis during a triadic interaction task, identifying coparental affect as a significant predictor of child emotion dysregulation. Like my prior review of parental depression, other unmeasured constructs may have impacted this association. Relationship quality strengthens the positive effect of parent-child interaction synchrony on child emotion regulation in both mothers and fathers (Kerr et al., 2021), highlighting how the effect of one subsystem can impact whole family dynamics (Belsky et al., 1996; Cox & Paley, 1997).

Limitations and Future Directions

First, the present study was limited in scope due to several self-imposed restrictions, such as only utilizing a SEM framework with distinguishable dyads and limiting comparison of multiple imputation to only listwise deletion and FIML. Other missing data treatments that could have been conducted for comparison purposes include expectation maximization (Dempster et al., 1977), single center imputation from multiple chained equations (Khan & Hoque, 2020), forms of single imputation like mean imputation or hot-deck imputation (Andridge & Little, 2010), or different methods within multiple imputations like random forests (van Buuren, 2022). Future research should take to conduct similar simulation studies on MLM models, as MLMs are more likely to suffer from misspecification when separating Level 1 and Level 2 variances (Keller & Enders, 2023). Additionally, the present study imposed missingness on simulated data using the MAR assumption, rather than MCAR, since multiple imputation may produce less biased results when working under the MAR assumption (Huque et al., 2018), so the present study's results may not generalize when data is MCAR.

Some issues may have originated from the data. In the FFCWS sample, parental depression was notably sparse due to the way the depression measure was administered to participants. Participants were only administered the depression measure if he or she answered yes to the question, “During past year, been time you felt sad or depressed for two or more weeks in row?”. If a participant answered no to that question, he or she was given a score of zero for all following CIDI-SF items. Additionally, few parents experienced major depression in the FFCWS sample. Only 17% of mothers and 12% of fathers met criteria for major depression using a liberal DSM-IV criteria (Bendheim-Thoman Center for Research on Child Wellbeing, 2019, p. 47). In future research on the FFCWS sample, researchers may consider creating a composite variable of general psychopathology to avoid sparseness.

Additionally, in the linear regression analyses, the final child outcome variable was reported by the family’s primary caregiver, which was overwhelmingly the child’s biological mother (Bendheim-Thoman Center for Research on Child Wellbeing, 2019, p. 76). Although prior research has demonstrated the effect of maternal parenting on child outcomes, this result is likely partially explained by both measures being reported by the same person (i.e., the mother). Alternative approaches include using data reported by the teacher as part of the FFCWS Kindergarten Study, although researchers only collected teacher data from 25% of participating families (Bendheim-Thoman Center for Research on Child Wellbeing, 2019, p. 12).

The present study has revealed several areas of investigation that were unable to be examined due to scope and time restraints. In the present study, missingness was imposed across the entire simulated dataset, but future research should examine missing data treatments specifically for the missing partner effect (Warner et al., 1979), which occurs when one partner is missing all data for a dyad. Specifically modeling the missing partner effect would have more adequately resembled the original FFCWS data as there were almost 24% fewer participating fathers compared to maternal participation (Bendheim-Thoman Center for Research on Child Wellbeing, 2019, p. 12). The missing partner effect was not modelled in the present study due to maximize the objective of comparing passive multiple imputation to other missing data treatments. Finally, the present study has identified several gaps in current statistical programming tools, such as the lack of support of multiply imputed data when calculating model fit (e.g., https://github.com/simsem/semTools/issues/113) or visualizing dyadic processes (e.g., https://stackoverflow.com/q/75573417/14992857).

Conclusions

In summary, the present study has reviewed prior research on dyadic and missing data analysis, built a pipeline for multiply imputing dyadic data with several different predictor matrices, and provided concrete examples of how to follow current best practices in multiple imputation, including passive multiple imputation and data transparency. The results of the quantitative portion revealed no notable differences regarding missing data treatments on different APIMs and linear regression models. Regardless, these results contribute to growing bodies of literature on multiple imputation and family systems theory.

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