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MISSING DATA IN FAMILY RESEARCH: EXAMINING DIFFERENT LEVELS OF MISSINGNESS

SEMIRA TAGLIABUE
CATHOLIC UNIVERSITY OF BRESCIA

SILVIA DONATO
CATHOLIC UNIVERSITY OF MILANO

Family research is influenced by the systemic nature of the family itself, so that missing data could be found at different levels (i.e., item, respondent, dyad). The aim of the study is to give family researchers a step-by-step description of the procedures used to analyze the amount of missingness and the mechanisms causing the missingness at the different levels featuring family data. Examples from two family datasets were provided and both individual and relational auxiliary variables related to the missingness were examined. The largest amount of missingness was found at the respondent level and, specifically, for the father's role. Regarding the missingness mechanism, missing completely at random (MCAR) was found for both dyad and respondent level missingness, whereas missing at random (MAR) could be hypothesized for missing data at the item level. The complexities inherent in family research levels and in family research planning, as well as future steps were discussed.

Key words: Missing data; Missingness mechanisms; Family research; Levels of missingness; Auxiliary variables.

Correspondence concerning this article should be addressed to Semira Tagliabue, Department of Psychology, Catholic University of Brescia, Via Trieste 17, 25121 Brescia (BS), Italy. Email: semira.tagliabue@unicatt.it

The study of family relationships challenges researchers with its high complexity. Indeed, family is an elaborated system composed by both individuals and subsystems (dyads, triads, tetrads) (Minuchin, 2002). Individuals have specific roles within the system: husband, wife, father, mother, offspring, grandmother, cousin, and so forth. Each role is defined within a relationship with another role: one person is a father not just by himself, but only if there is someone who is a son or a daughter. Moreover, the family system is also composed by dyadic relationships or by subsystems (as the one composed by the two parents and the child). Although most family research still focuses on the individual unit of analysis, thus failing to capture the systemic nature of the family itself (Lanz, Scabini, Tagliabue, & Morgano, 2015), studies on family issues and relationships may involve research questions pertaining to different units of analysis within the family: the individual (e.g., "Is the father more depressed after childbirth?"), the dyad (e.g., "Does the quality of parent-child relationships affect fathers' parenting styles?"), the family (e.g., "Do more cohesive families promote children's sense of autonomy?"), or a combination of the three (e.g., "Does the quality of parent-child relationships affect the child's risk behaviors differently depending on the level of family cohesion?").

Family research is often conducted by collecting non-independent data that feature family members' interdependence. Indeed, when family processes and characteristics are studied with quan-

titative data, collecting multiple perspectives on the family itself by different family members helps researchers to answer questions regarding the family as a system (Cook & Dreyer, 1984; Lanz et al., 2015). The richness inherent in collecting data from multiple family members is, on the other side, difficult to analyze. Numerous techniques have been developed to handle the non-independence of dyadic and group data as well as to use non-independence as a source of relational information (Kenny, Kashy, & Cook, 2006; Tagliabue & Lanz, 2009, 2014). Little literature still exists, however, on a basic problem for family research, that is, handling missing family data. Handling missing data allows researchers to obtain less biased and more accurate findings as well as to increase statistical power by using all the available information (Newman, 2014). Missingness in family research, in particular, could be distinguished into different levels: item level, respondent level, and dyad level. Item level missingness means that a specific item is missing for one or more respondents.[1] Thus, for each family member (respondent) it is possible to identify an amount of missingness at the item level. Missingness at the item level is the most commonly discussed in missing data literature and is not specific of family research, although the presence of more than one respondent in many family studies requires item missingness to be considered for each respondent.

Missingness at the respondent level, instead, is specific of family and relational research, and means that the whole questionnaire of one respondent is missing (Kalmijn & Liefbroer, 2011; Young & Johnson, 2013). While in research on individuals it is very difficult (if not impossible) to analyze this type of missingness (Newman, 2014), in family research it is possible to examine respondent missingness when we have data from more than one respondent and the other family member(s) may provide information about the missing respondent. Another level of missingness that is typical of family and relational research is missingness at the dyad level. Missingness at the dyad level means that some dyads within the family do not provide data on the whole questionnaire, so that both members of a dyad are missing.

Only a few resources have provided discussions that can be relevant to family missing data. In particular, some contributions have focused on the so-called "secondary respondent" missingness (e.g., missing data from nonresident adult children of primary respondents) (Kalmijn & Liefbroer, 2011; Young & Johnson, 2013). Kalmijn and Liefbroer analyzed the variables related to nonresponse (individual characteristics of the respondent, relational characteristics, and interview experiences) and applied ordinary least square (OLS) and Heckman's sample selection model to investigate the amount of bias affecting estimates. Young and Johnson, instead, compared five different methods (i.e., complete case analysis, inverse probability weighting, Heckman's selection model, maximum likelihood estimation-ML, and multiple imputation-MI) to treat secondary respondent missing data, showing that ML and MI produced less biased estimates.

These existing sources, however, did not provide detailed guidance for family researchers in the first step of missing data management, that is, the analysis of the amount of missing data and the identification of the relevant causes of missing data (i.e., missing data mechanisms). More specifically, existing sources did not discuss how to analyze missingness at different levels of family missing data (i.e., item, respondent, and dyad). Such a first step is indeed essential for both theoretical and practical reasons. Theoretically, it helps family researchers to gain knowledge on the complexities of their data patterns and on the specificities of family research designing. Practically, it is necessary to analyze the missing data mechanisms at the levels of interest to make informed decisions on how to treat this issue in one's research.

The present study aims to give family researchers a step-by-step description of the procedures used to analyze, at each level, the amount and type of missingness mechanism that are typical of family research. In particular, the procedures to examine missingness in family research are described by taking into account three possible levels of missingness: the item level, the respondent level, and the dyad level. First, we provide a brief introduction on the most classic terms used to describe the types of missingness mechanisms responsible for the pattern of non-response. Second, we describe how these mechanisms apply to the different levels considered. Finally, we present two example studies in which we analyze the amount of missingness and the missingness mechanisms at each level.

Missingness Mechanisms

Rubin (1976; Little & Rubin, 2002) identified three mechanisms explaining missingness that have become foundational in the description of missing data and their treatment. They are missing completely at random (MCAR), missing at random (MAR), and not missing at random (NMAR). Rubin (1976) defined as missing completely at random the mechanism in which missing values on a variable *Y* are unrelated to all the other observed variables in the dataset as well as to the underlined values of the *Y* variable itself. As an illustration, imagine a two-wave longitudinal study on adjustment in adolescents conducted at school. Data would be considered MCAR if some adolescents did not complete some items for some random factors: they might have skipped one page of the questionnaire by mistake, or they might have not completed the second assessment because of illness or relocation. If these factors were not related to any other variable measured in the study (e.g., socio-economic status — SES; level of adjustment at Time 1; etc.) as well as to any other unmeasured variable, the pattern of missingness present in the dataset would be considered random. This means that the observed scores represent a random sample of the entire sample and that analyses conducted on complete cases would not be biased.

The term missing at random is used to describe a mechanism in which the likelihood of missing data on a variable *Y* is related to another observed variable in the dataset, but not to the values of *Y* itself, thus under the MAR condition, the missingness can depend on observed variables but not on unobserved ones (i.e., the missing data on *Y*).[2] For example, imagine that the adolescents from the previous example had to respond to an item asking whether they were interested in participating in volunteering groups (variable *Y*) and that they were asked somewhere else in the study whether they were members of charity associations (variable *X*). The probability of missingness on *Y* may be different in the group of adolescent already part of charity associations from the probability in the group of adolescent that were not part of charity groups (variable *X*), so that for example the adolescents already involved in charity work were more likely to omit the item on their interest in volunteering because they were already volunteering. In this case, missingness on volunteering is related to the adolescents' response on charity participation, but not related to the adolescents' interest in volunteering. This also means that within each *X* subgroup (charity participation vs. no charity participation) the pattern of missing data on *Y* is random.[3]

Missing mechanism is said to be non-ignorable (Little & Rubin, 2002) or not missing at random (Graham, 2009; Schafer & Graham, 2002) when the likelihood of a variable score being missing is related to the score on that same item. In other words, non-ignorable missingness is due

to some unobserved factor not accounted for by other measured variables in the study. Note that NMAR cannot be evaluated and it is more a matter of a conceptual consideration: how likely is that a participant with high (or low) scores on a this variable would omit the item or leave the study? As an example, it may be that adolescents who are more (or less) sexually active would skip an item asking about their sexual relations because they may be uncomfortable with others knowing this aspect of their life. In this case, missing values on sexual relations are directly related to the adolescents' sexual activity. Importantly, the three mechanisms are not mutually exclusive, but all three of them can be found in a given dataset (Newman, 2014). Following Graham (2009), "the best way to think of all missing data is as a continuum between MAR and MNAR" (p. 567).

The main consequence of MCAR is loss of statistical power, in that the MCAR condition does not affect parameter estimates, which are in this case unbiased (i.e., close to the population values). The MAR condition produces unbiased estimates as well, once the variables related to the missingness are controlled for. NMAR, instead, produces biased parameters and is therefore considered a problem for statistical analyses. In the next paragraph we will turn to the way the above mechanisms can apply to the different levels of family research missing data.

Missingness at Different Levels

The three mechanisms of missingness (MCAR, MAR, and NMAR) can be applied to the three different levels of missingness. Examples of the application of missingness mechanisms at the item level were presented in the previous paragraph. In this paragraph we provide examples regarding the respondent and dyad levels. With regard to the application of the three missingness mechanisms to the respondent level, imagine that the adolescents of the research on adjustment described above were also asked to involve their parents in the study and to give them a questionnaire regarding their working conditions. Indeed, the researchers' hypothesis was that the parents' work satisfaction could be linked to the adolescent's adjustment. In this case, data from the parents may be missing at the respondent level, that is, some family unit may not have data from one of the two parents.

In this case, data would be considered MCAR if the parent did not complete their questionnaire because of some random factors, unrelated to the other observed variables: for example, he/she was away from home for a family celebration (e.g., wedding). To illustrate the MAR condition, imagine we missed one respondent in the parents' data, for example the father, and somewhere else in the study (e.g., in the adolescent's questionnaire) we had data on the relationship between the adolescent and the father. If the father's missingness was related to the relationship with the adolescent, the probability of the father's missingness may be different in the group of adolescents with a good relationship with their fathers from the probability in the group of adolescents with a poor relationship with their fathers, so that, for example, the adolescents with poorer relationships with their father were more likely not to involve him in the study. In this case, missingness on the father's questionnaire is related to the adolescents' response on father-child relationship quality, but not to the father's working conditions measured in the father's questionnaire. This also means that within each subgroup (good vs. poor father-child relationship) the pattern of missing data is random on the variable of interest. Finally, the father's data are to be considered NMAR if, for example, unemployed fathers refused to respond to the questionnaire or their children omitted to handle the

questionnaire to them since they did not want to upset them. In this case, the father's missingness is directly related to the variable(s) assessed in his questionnaire.

With regard to the dyad level, imagine that some mother-father dyads did not provide data on the whole questionnaire. Data would be considered MCAR if both the father and the mother did not complete these measures because of some random factors unrelated to the other observed variables (e.g., the adolescent left the envelope with the two questionnaires on the bus). The MAR condition would apply, for example, if the father and the mother did not respond on the questionnaire because they are upset and embarrassed about their poorly adjusted child (e.g., he/she smokes, is involved in bullying, etc.). In this case, missing dyad data are MAR because the probability of missingness is related to the child's adjustment (an observed variable), but not to the parents' working conditions. Finally, dyad data could be NMAR if, for example, one parent is unemployed and the other is working overtime to sustain the family finances and they may not be willing or may not have time to participate in the study. In this case, dyad data are NMAR because missingness is directly related to the dyad's working conditions.

Testing Missingness Mechanisms

To find out whether missing data are MCAR, MAR, or NMAR, together with theoretical considerations, some statistical procedures can be used (e.g., Schlomer, Bauman, & Card, 2010): Little's (1988) test and correlations with potential auxiliary variables (i.e., variables potentially associated to the missingness). Little's test is an omnibus test that evaluates the null hypothesis that missing data are MCAR. The main idea of the test is to evaluate whether or not cases that share the same missing data pattern present mean differences in the other variables considered. When the test is significant, the possibility of MAR or NMAR should be considered. Being an omnibus test, Little's test is used to explore missingness on the whole set of variables considered. This means that it is not possible to identify which variables are characterized by MCAR, and which by MAR. The test only assesses whether there is a MCAR pattern in the chosen set of variables. To the best of our knowledge, there is not a rule related to the choice of variables to be included in the test, so two possible strategies can be used. The first is to include only the variables that compose the model to be analyzed. In that case, if MCAR is supported by the test, analyses on the model can be conducted without being worried by the bias of the estimates. The second strategy is to include all the variables of the dataset (both model variables and potential auxiliary variables). This strategy is suggested in all cases in which the researcher would like to globally explore the missingness pattern in the whole data set. Indeed, it is highly possible that not only model variables present missing data, but also auxiliary variables may be missing, and/or it is also possible that the same auxiliary variables could become model variables in following studies on the same dataset. In the present paper, both strategies are presented.

Being an omnibus test, Little's test cannot provide information about a single variable missingness mechanism, so another procedure should be used to investigate whether the presence of missing data at each level is linked to some other observed variables (auxiliary variables) in the dataset (i.e., to test the MAR hypothesis). Testing the association between missingness and auxiliary variables could allow to adopt the adequate missing data management procedures and, as a consequence, to increase power and decrease bias (Enders, 2010). If the pattern of missingness con-

sidered is not related to any other observed variables, missing data should be considered either MCAR or NMAR. If the missingness is associated to one or more variables in the dataset, missing data should be considered either MAR or NMAR. Importantly, the identification of observed variables associated to the missingness (i.e., auxiliary variables) can be used not only to examine the type of missingness mechanism, but also to implement some of the most recommended procedures of missing data management (e.g., full information maximum likelihood-FIML and multiple imputation-MI). To identify auxiliary variables, the presence of missingness at the level of interest[4] should be measured with a dummy variable with 0 representing the absence of missing data and 1 the presence of missing data. Then, the relation between that dummy variable and the variables eligible for being auxiliary variables should be tested. In family research, auxiliary variables could be individual variables (i.e., variables that measure individual characteristics of family members), relational variables (i.e., variables that measure relational characteristics of family dyad), and family variables (i.e., variables that measure characteristics of the whole family).

Finally, it is noteworthy that the possibility of NMAR could only be excluded on the basis of theoretical considerations. It is common to exclude NMAR when there are no theoretical reasons to assume it and there are no empirical indications of the contrary (e.g., a significant Little's test and no associations between the missingness and other observed variables). The choice of auxiliary variables usually depends on theoretical considerations or previous research findings. Alternatively, associations can be tested empirically between the missingness and all possible auxiliary variables in the dataset (Enders, 2010). For a purpose of exemplification, in the present paper we used an inclusive strategy and tested all the variables not included in the model as potential auxiliary variables (Collins, Schafer, & Kam, 2001).

Examples

The aim of the present study was to provide a step-by-step description of the procedures used to analyze a) the amount of missingness at the different levels considered (item, respondent, and dyad) and b) the mechanisms assumed to be responsible for the missingness (MCAR, MAR, or NMAR). To this aim, we used data from two different family research datasets. The first dataset referred to a study on family relationships, in which young adult children were asked to fill in the questionnaire and to involve their parents in the research (family dataset). The second dataset referred to a study on marital relationships, in which premarital partners were asked to involve their parents in the study. In this paper, we focused on the partners' parental couples data (parental couple dataset). Imagine that in both studies the researchers were interested in testing the same theoretical model: relationship satisfaction within dyadic family relationships (marital relationship or parent-child relationship) is predicted by self-esteem and life satisfaction. These three constructs (relationship satisfaction, self-esteem, and life satisfaction) were measured in both studies and each study also assessed several other constructs together with socio-demographic variables. Analyses were performed using SPSS 19, as one of the most commonly used statistical packages for social scientists. Most analyses performed in the present work, however, are basic options available in most statistical packages used by family researchers.

METHOD

Family Dataset

Participants

Two hundred and thirty-seven families composed by father, mother, and young adult child were recruited for the study. Young adults were contacted in one of the universities of Milan (Italy). They were all about to conclude their Master degree (34.8% males and 65.2% females; mean age 26.49, *SD* = 2.00). They were asked to involve in the research project also their father, mother, one sibling (if they had one), one friend, and the romantic partner (if they had one). For the purpose of the present research, only the triads composed by father, mother, and young adult child were considered. Among those families, 93.9% of young adults reported to have both parents, whereas 0.9% reported to have only the father, and 5.2% only the mother. Fathers' mean age was 57.16 (*SD* = 4.85) and mothers' mean age was 54.15 (*SD* = 4.80). All the young adults were Italian and most of them lived in families with a middle-high socioeconomic status; more specifically, 4.9% of them lived in families that earned €500 to 1.000; 21.5% lived in families earning €1.000 to 2.000; 29.3% in families with a household income of €2.000 to 3.000; 44.4% in families that earned €3.000 to 5.000 or more.

Procedure

Young adults were recruited through their Master thesis advisors or through the university secretariats. Upon verification of inclusion criteria, with a telephone call or via e-mail, participants were invited to the lab. During the appointment, research aims and structure were explained and participants' inquiries were answered. A folder with three questionnaire versions was delivered, with one questionnaire version for each person involved in the research: father, mother, and young adult. Each questionnaire was in one envelope for each family member containing an explanation letter with contacts to call for any further questions and an informed consent form to sign before filling in the questionnaire. Anonymity was guaranteed and a second appointment to return questionnaires was scheduled. Usually 10 to 15 days were necessary to complete the questionnaires. Further details on the whole research project can be found in Tagliabue (2006).

Measures

Participants provided demographic information and filled in several self-report instruments. The three self-report instruments considered in the present paper were the following.[5]

Rosenberg Self-Esteem Scale (Rosenberg, 1965). The scale measures self-esteem and is composed of nine items. Sample item: "I feel that I have a number of good qualities." Items were measured on a 5-point scale (from 1 = *completely disagree* to 5 = *completely agree*). By averaging the nine items we obtained a self-esteem index for each family member ($.78 < \alpha < .84$).

Satisfaction With Life. One single item was used in order to evaluate life satisfaction: "How much are you satisfied with your life in general?" Answers were provided on a 10-point scale (from 1 = *completely disagree* to 10 = *completely agree*). The measurement of satisfaction with life was obtained for each family member.

Relationship satisfaction (Furman & Buhrmester, 1985). It is a three-item measure of relationship satisfaction. Items used a 5-point scale (from 1 = *completely disagree* to 5 = *completely agree*). Sample item: "How happy are you with your relationship?" By averaging the three items we obtained a relationship satisfaction index for each family member's perception of his/her family relationships ($.90 < \alpha < .96$).

Parental Couple Dataset

Participants

Three hundred and fifty-eight parental couples were invited to participate in a study via their young-adult sons or daughters who were getting married. Participants were mostly married (92.9%) and their average duration of marriage was 34.02 years (*SD* = 6.06). Mothers' mean age was 58.01 (*SD* = 7.08) and fathers' mean age was 60.76 (*SD* = 6.93). As for years of education, 64.31% of mothers and 55.70% of fathers had up to eight years, 30.68% of mothers and 37.79% of fathers reached up to 12/13 years (depending on the type of high school), 5.01% of mothers and 5.21% of fathers completed 16 years of education and only 0.98% of fathers completed more than 16 years. As for household income, 26.9% of parents reported an income at or below €1.500 per month, 53.5% of parents between €1.500 and €3.000, 15.4% of parents between €3.000 and €5.000, and 4.3% of parents over €5.000.

Procedure

Participants were recruited as part of a project on the transition to marriage in which premarital partners were asked to involve their parents in the study whenever possible and were given a packet of questionnaires (one for each partner in the premarital couple and one for each partner in their parents' couples), together with instructions to complete the questionnaires independently. All participants signed an informed consent form and were not paid for their participation in the study, as is common in Italy. Further details of the sample and procedure can be found in Iafrate, Bertoni, Donato, and Finkenauer (2012).

Measures

In addition to providing demographic information and several other self-report measures,[6] participants completed a self-report questionnaire including the following scales:

Rosenberg Self-Esteem Scale (Rosenberg, 1965; Italian translation by Prezza, Trombaccia, & Armento, 1997). The scale measures self-esteem and is composed of 10 items, measured

on a 4-point scale (from 1 = *completely disagree* to 4 = *completely agree*). Sample item: "I think I have a number of qualities" ($\alpha \geq .77$).

Satisfaction With Life Scale (Diener, Emmons, Larsen, & Griffin, 1985). It is a five-item scale measuring the individual's satisfaction in several domains of life. Items are measured on a 7-point scale (from 1 = *completely disagree* to 7 =*completely agree*). Item example: "I'm satisfied with my life" ($\alpha \geq .93$).

Quality of Marriage Index (Norton, 1983). It is a six-item measure of couple satisfaction. Five items use a 7-point scale (from 1 = *completely disagree* to 7 = *completely agree*; sample item: "The relationship with my partner makes me happy") and the last item, measuring a global perception of couple satisfaction ("Cross the number that better identifies how happy you feel in your relationship"), a 10-point scale (from 1 = *very unhappy* to 10 = *very happy*) ($\alpha \geq .85$).

Data Analyses

Amount of Missingness at the Different Levels

Although in typical applications of missing data analysis (even in family studies) the amount of missingness is examined at the item (or construct) level, in the present paper we purposely examined missingness at the different levels typically present in family research. Therefore, for the purpose of analyzing the amount of missingness at each level, we proceeded backwards (from the dyad level to the item level), so as to control for the higher level of missingness when computing the amount of missing data at the lower level. Indeed, missing data on one item could be due to the fact that the whole questionnaire of the respondent is missing. Thus, controlling for higher level missingness would allow to consider the amount of missingness that is specific of each level.

In sum, we first computed the amount of family units in which two family members did not fill in the whole questionnaire (dyad level missingness). For instance, there could be dyad level missingness for the parental dyad in the family if the father and the mother of a family did not fill in the questionnaire, but the child did. Then, controlling for the missingness at the dyad level, the number of family or couple members who did not respond to their entire questionnaire represented the amount of missingness at the respondent level. Finally, we considered the missingness at the item level. Controlling for the missingness at the respondent level, the amount of missing data for each item of the scales of interest was computed.

Missingness Mechanisms

To test the type of missingness present in the data (MCAR, MAR, or NMAR), the following procedures were applied. Little's test was applied to test the MCAR hypothesis, adopting two different options, as described above: considering the model variables only and the whole dataset. Using SPSS 19, we used the missing value analysis (MVA) command. The variables of interest should be entered in the variable box according to their measurement scale, and the expectation maximization (EM) algorithm should be selected. In the output, the result of the Little's

test would be displayed below the EM estimated statistics. The null hypothesis of the test is that the missing data are MCAR. Little's test, by definition, applies to the item level of missingness.

To test whether MAR was a possible explanation for the missingness, we created dummy variables in which 0 represented cases in which no missing data were present, and 1 represented cases in which there were missing data at the level of interest. Then, correlations between the dummy variables and the potential auxiliary variables in the dataset were analyzed. Sociodemographic variables, individual, and relational variables were considered and included in the analyses (we did not include family variables because in the example datasets there were no family variables). If significant links between each dummy variable and the auxiliary variables were found, then missing data on that variable could be considered MAR. Given the limitations of Little's test, it should always be complemented by the investigation of the links between dummy variables and potential auxiliary variables.

RESULTS

Amount of Missingness at the Different Levels

Family Dataset

Missing data at the dyad level were: 5.90% for the marital dyad, and 0.40% for the father-child and mother-child dyads. Controlling for the missingness at the dyad level, missing data at the respondent level were 10.40% for fathers, followed by mothers (3.20%). There were no missing data at the respondent level for the young adult child. Controlling for dyad and respondent missingness, we computed missingness at the item level, separately for each respondent, referring to the 17 items of the variables of interest. Ranges of missingness at the item level are shown in Table 1.

TABLE 1
Amount of missingness at different levels

Dataset	Family/dyad member	Missingness at dyad level	Missingness at respondent level	Missingness at item level
Family	Father	FM: 5.90% FC: 0.40%	10.40%	3.00-9.50%
	Mother	FM: 5.90% MC: 0.40%	3.20%	1.40-6.40%
	Young adult child	FC: 0.40% MC: 0.40%	0.00%	0.40-7.20%
Dyadic	Father	–	10.33%	0.93-8.72%
	Mother	–	1.39%	3.68-12.75%

Note. FM = marital dyad; FC = father-child dyad; MC = mother-child dyad.

Parental Couple Dataset

With regard to respondent missingness, in five out of 358 couples (1.39%) the woman was missing, while in 37 couples the man was missing (10.33%). At the item level, once controlled for respondent missingness and referring to the 21 items of interest, women presented on average 5.34% (range 3.68-12.75) of missing data at the item level and men presented on average 4.26% (range 0.93-8.72) of missing data (see Table 1).

Missingness Mechanisms

Family Dataset

Little's test on the model variables showed that the pattern of missingness could not be considered MCAR, $\chi^2(2112) = 2273.60$, $p < .01$, whereas the test conducted on the whole data resulted to be nonsignificant, $\chi^2(60105) = 33630.66$, $p > .05$. In order to evaluate which auxiliary variables could be associated with the missingness pattern of model variables at each of the three levels, we correlated the missingness dummy variables with auxiliary variables. Three types of auxiliary variables, for a total of 42 variables, were used: individual variables (e.g., sense of coherence, self-efficacy), dyadic/relational variables (e.g., support, conflict, differentiation, commitment, influence), and sociodemographic variables (e.g., gender, age, education). No significant associations between auxiliary variables and missingness at the dyad level were found. Both MCAR and NMAR could be hypothesized.

Regarding missingness at the respondent level, no significant associations between auxiliary variables and missingness were found, denoting both MCAR or NMAR mechanisms. The associations with young adult respondent missingness were not displayed because no missing data were found for that respondent. Regarding missingness at the item level, most associations resulted to be nonsignificant, but each item missingness was significantly associated with at least one auxiliary variable, so that a MAR pattern could be hypothesized. As shown in Tables 2 and 3, significant associations were all weak.

Parental Couple Dataset

Little's test, conducted both on model variables, $\chi^2(2039) = 2331.46$, $p < .001$, and on the whole dataset, $\chi^2(88914) = 81784.54$, $p > .05$, showed that the pattern of missingness did not deviate from MCAR. Next, we correlated the dummy variables with the variables selected as potential auxiliary variables. In the parental couple dataset we selected 49 potential auxiliary variables of the following types: dyadic/relational variables (e.g., intimacy, passion, forgiveness; Table 4), individual variables (e.g., depression, religiosity, health conditions; Table 5), and sociodemographic variables (e.g., age, education, income; Table 6).

TABLE 2
Correlations between dummy missing variables at respondent and item levels and relational auxiliary variables (Family dataset)

	Respondent level missingness		Item level missingness		
	Father	Mother	Father	Mother	Child
SupportCF	.01	–.08	–.12~ –.04	–.15*~.12	–.05~.11
SupportCM	.00	–.03	–.14~.04	–.24**~.08	–.03~.07
SupportFC		–.04	–.22**~.12	–.12~.10	–.08~.08
SupportMC	.00		–.07~.00	–.10~.06	–.04~.02
SupportFM		–.01	–.18*~ –.03	–.13~.05	–.10~.12
SupportMF	.02		–.16*~.00	–.13~.03	–.02~.05
ConflictCF	.05	.09	–.04~.06	–.07~.09	–.07~.17*
ConflictCM	.01	–.09	–.09~.11	–.05~.18*	–.02~.14*
ConflictFC		.10	–.06~.13	–.11~.09	–.04~.10
ConflictMC	–.02		–.04~.15*	–.03~.19**	–.01~.09
ConflictFM		.04	–.07~.07	–.05~.13	–.07~.09
ConflictMF	–.02		–.03~.16*	–.05~.09	–.13~.07
DifferentiationCF	.09	–.07	–.21**~.03	–.06~.12	–.13~.08
DifferentiationCM	.02	–.05	–.14*~ –.01	–.04~.16*	–.15*~.05
DifferentiationFC		–.16	–.21**~ –.07	–.06~.13	–.04~.09
DifferentiationMC	.00		–.08~ –.02	–.16*~.08	–.09~.08
DifferentiationFM		–.07	–.12~.00	–.09~.10	–.09~.05
DifferentiationMF	.03		–.12~.02	–.15*~.08	–.02~.07
CommitmentFM		.00	–.07~.09	–.10~.08	–.11~.07
CommitmentMF	–.09		–.07~.12	–.12~.05	.03~.07
InfluenceCF	.02	–.10	–.03~.10	–.03~.09	–.14*~.14*
InfluenceCM	–.10	–.09	.07~.14*	–.09~.08	–.13~.10
InfluenceFC		–.02	–.06~.00	–.11~.14	–.13~ –.02
InfluenceMC	.03		.04~.12	–.18**~.15*	–.06~.13*
InfluenceFM		–.08	–.04~.10	–.09~.11	–.08~.02
InfluenceMF	–.04		–.01~.10	–.19**~.14	–.09~.09

Note. FM = father's perceptions on relationship with mother; FC = father's perceptions on relationship with young adult child; MF = mother's perceptions on relationship with father; MC = mother's perceptions on relationship young adult child; CF = young adult child's perceptions on relationship with father; CM = young adult child's perceptions on relationship with mother.
*$p < .05$. **$p < .01$.

TABLE 3
Correlations between dummy missing variables at respondent and item levels and individual or sociodemographic auxiliary variables (Family dataset)

	Respondent level missingness		Item level missingness		
	Father	Mother	Father	Mother	Child
EfficacyC	–.16	.07	–.05~ –.01	–.01~.10	–.05~.11
EfficacyM		–.03	–.06~.05	–.12~.05	–.02~.08

(table 3 continues)

Table 3 (continued)

	Respondent level missingness		Item level missingness		
	Father	Mother	Father	Mother	Child
EfficacyF	–.04		–.04~.10	–.19**~.11	–.05~.13
Sense of coherenceF	–.06		–.12~.02	–.03~.06	–.14~.08
Sense of coherenceC	–.04	.02	–.08~.02	–.09~.12	–.16*~.10
Sense of coherenceM	–.23	.06	–.21**~ –.08	–.19**~.09	–.03~.10
EducationC	–.04	–.02	–.09~.06	–.10~.06	–.13~.22**
GenderC	–.06	–.02	–.08~.10	–.08~.10	–.18**~.07
AgeC	–.11	–.01	–.13~ –.07	–.07~.19**	–.12~.05
EducationF	.05		–.05~.12	–.12~.10	–.08~.13
EducationM		–.03	–.06~.04	–.18*~ –.01	–.09~.06
AgeF	–.04		–.12~.00	–.01~.17*	–.09~.16*
AgeM		.08	–.17*~.06	–.11~.17*	–.14*~.07
Number of family members	.05	–.19	–.11~.14	–.30**~.05	–.21**~.07
Number of family members who earn money	.01	–.11	–.04~.05	–.23**~.08	–.16*~ –.01
Income	–.05	–.19	–.19*~.08	–.27**~.01	–.18**~.14*

Note. C = child; M = mother; F = father.
*p < .05. **p < .01.

TABLE 4
Correlations between dummy missing variables at respondent and item levels and relational auxiliary variables (Parental couple dataset)

	Respondent level missingness	Item level missingness	
	Father	Father	Mother
Quality of relationship with premarital partners mother	–.03	–.03~.12*	–.04~.11*
Quality of relationship with premarital partners father		–.11*~.00	–.04~.09
Unforgiveness mother	–.12	.02~.19**	.01~.15**
Unforgiveness father		–.08~.01	–.10~.04
Benevolence mother	–.15	–.05~.14*	–.03~.09
Benevolence father		–.05~.03	–.01~.07
Positive dyadic coping mother	–.06	–.13*~ –.02	–.07~.06

(table 4 continues)

Table 4 (continued)

	Respondent level missingness	Item level missingness	
	Father	Father	Mother
Positive dyadic coping father		–.05~.03	–.08~.02
Negative dyadic coping mother	.02	–.02~.18**	–.01~.11*
Negative dyadic coping father		–.02~ .18**	.06~.17**
Common dyadic coping mother	–.18**	–.06~.00	–.02~.17**
Common dyadic coping father		–.03~.06	–.12*~.06
IOS mother	–.16**	–.14*~.05	–.11*~.08
IOS father		–.04~.09	–.08~ –.01
Passion mother	–.25**	–.12*~.08	–.13*~.09
Passion father		–.02~.07	–.03~.08
Intimacy mother	–.30**	–.09~.06	–.10~.05
Intimacy father		–.05~ –.07	–.10~.03

Note. IOS = Inclusion of the other in the self.
*$p < .05$. **$p < .01$.

TABLE 5
Correlations between dummy missing variables at respondent and item levels and individual auxiliary variables (Parental couple dataset)

	Respondent level missingness	Item level missingness	
	Father	Father	Mother
Social support (availability) mother	.03	–.06~.14*	–.06~.10
Social support (availability) father		–.05~.13*	–.09~.01
Social support (actual) mother		.00~.12*	–.07~.09
Social support (actual) father		–.08~.12*	–.11~.02
Size of social network mother	–.18**	–.13~.13	–.12~.06
Size of social network father		–.06~.15	–.12~.10
Generativity mother	.10	–.07~.04	–.20**~.10
Generativity father		.00~.14*	–.04~.12*
Depression mother	.02	–.04~.09	–.09~.06
Depression father		.10~.24**	–.08~.14*
Religious practice mother	.00	–.05~.03	–.05~.05
Religious practice father		–.06~.14*	–.02~.12*
Religiosity mother	–.02	–.03~.04	–.06~.04
Religiosity father		–.03~.13*	–.04~.05
Health condition mother	.10	–.05~.06	–.04~.09
Health condition father		.02~.11*	–.01~.17**

*$p < .05$. **$p < .01$.

TABLE 6
Correlations between dummy missing variables at respondent and item levels and sociodemographic auxiliary variables (Parental couple dataset)

	Respondent level missingness	Item level missingness	
	Father	Father	Mother
Age mother	.15**	–.10~.14*	–.00~.13*
Age father		–.06~.15**	–.06~.09
Years married	.13*	–.13*~.17**	–.00~.19**
Number of children mother	.03	–.08~.06	–.10~.01
Number of children father		–.07~.06	–.07~.01
Age first child mother	.16**	–.13*~.16**	–.04~.20**
Age first child father		–.09~.14*	–.07~.12*
Number of siblings mother	.08	–.02~.13*	–.05~.09
Number of siblings father		–.04~.08	–.05~.08
Income mother	–.22**	–.12~.05	–.20**~.03
Income father		–.12~.10	–.16*~ –.04
Mother's health condition (mother)	.12	–.01~.18*	–.06~.11
Mother's heath condition (father)		–.12~.13	–.13~ –.01
Father's health condition (mother)	.08	–.15~.21	–.15~.15
Father's health condition (father)		–.11~.07	–.21~.06

*$p < .05$. **$p < .01$.

Significant associations were found for the father's respondent missingness, in particular with relational variables: the lower was the quality of the couple relationship as reported by the mother, the higher the amount of missing fathers' data. In addition, also sociodemographic variables were significantly related to the father's respondent missingness: fathers' missingness increased with the stage of the relationship (in terms of the woman's age, the years of marriage, and the age of the first child), whereas decreased with socioeconomical resources (size of social network, income). In this case, MAR could be presumed. The associations with mothers' respondent missingness was not displayed because of lack of missing data for that respondent. Regarding missingness at the item level, each item missingness was significantly associated with at least one auxiliary variable denoting a MAR pattern, though associations were mostly weak.

DISCUSSION

What Did We Learn?

The overall aim of the present study was to present, step-by-step, how to investigate the pattern of missingness at the three different levels (item, respondent, and dyad) within two different family research datasets. In the first dataset, three family members were involved (young adults and their parents), whereas the second dataset was composed by the two partners of a couple. Regarding the

amount of missingness at the different levels, respondent and item levels are the ones with higher percentage of missingness for both datasets. In the family dataset, missingness at the dyad level is very low, indicating that, when a family triad is involved in a research study, it is not frequent to miss two out of three family members. In our family example, the parental dyad has the highest percentage of missingness at the dyad level, probably because mothers and fathers were not directly contacted by the researchers, but they were contacted only indirectly through the mediation of the young adult child. At the respondent level, in both family and parental couple datasets, fathers present a higher amount of respondent missingness than mothers, confirming the specific difficulty to involve male respondents in psychological and family research (Costigan & Cox, 2001). Moreover, especially in the family dataset, it is possible that the father received a "third-hand" invitation to participate: young adult child asked the mother, who in turn asked the father. The lowest percentage of respondent level missingness is the one referred to the young adult child in the family dataset. This finding could be explained by the fact that he/she was the direct contact of the researcher. The data collection plan is particularly influential for the respondent level missingness, and consequently for dyad level missingness, in that a direct contact can help to increase respondents' participation rate, and may determine which dyad will be most likely to have missing data.

Thus, the present findings highlight the importance of accurately planning data collection when family or dyad members are involved in a research study. The most effective, though very burdensome strategy, seems to contact directly all the family members in order to increase participation and decrease missingness. An alternative strategy could be to focus on the most relevant dyad for the research aims and get in contact with both members of that dyad. For instance, if the main research question in a family study is about the marital couple, one could contact both partners of the couple and ask them to invite the children. Another strategy could be to rotate the family member to contact during data collection across families. This procedure would avoid the risk that one type of dyad or respondent is under-represented in the sample. For example, in a research on heterosexual couples, researchers could contact the male partner for half of couples, and the female partner for the other half.

When item missingness is considered, there is high variability in the percentage of missingness across items. To decrease missingness at this level classical suggestions about the length of questionnaires, the item order, and so forth, should be considered (Chiorri, 2011). The only specificity related to family research, however, is the percentage of item missingness in relational items. For example, when the father is missing, it is more likely that the young adult would not respond to the quality of communication with him than to a self-esteem item.

Beyond practical considerations regarding statistical power and accuracy of estimates, the analyses referring to the amount of missingness are also useful theoretically because they allow to understand at what level the missingness is particularly relevant. The distinction among levels of missingness is not always relevant in terms of the statistical techniques used to diagnose and treat missing data, as in some cases the same procedures can be used for different levels (Young & Johnson, 2013). This distinction, however, is still important for theoretical reasons and for its practical implications for research design and data collection. In reporting the amount of missingness of a study, we recommend family researchers to present the amount of missingness at different levels. Then, the analysis of the missingness mechanisms can be performed at the level(s) of interest (item, respondent, and dyad), depending on the purpose of the research.

As for the examination of mechanisms responsible for the missing data, in both example studies presented Little's test showed that the pattern of missingness was MCAR if tested on the model variables while seems not to deviate from MCAR if tested on all the variables in the dataset. Regarding the associations with auxiliary variables, findings showed variability according to the level of missingness considered. Unless researchers have reasons to hypothesize NMAR, both dyad and respondent level missing data could be considered MCAR. The only exception is the father's respondent missingness in the parental couple dataset that can be considered MAR. Finally, MAR patterns could be presumed in all items, as indicated by the associations between the missingness at the item level and the auxiliary variables. With regard to this, socio-demographic, individual, and relational variables result to be related to the missingness, showing the composite sources of it, in line with the systemic nature of the family, in which different levels of dynamics (individual, dyadic, and group) show reciprocal influences. It is also worth noting that the correlations are quite weak and differ according to the variable considered. Indeed, some authors suggested that variables with correlations below .40 should not be included in imputation procedures (e.g., ML and MI) as auxiliary variables because they would not decrease bias and increase power to a significant extent (Collins et al., 2001; Enders, 2010). The complexity of family or couple research is evident also in the analysis of missingness mechanisms that differ according to the level considered, requiring researchers to adopt missing data management strategies suited to the mechanism found at the level of interest.

Where Do We Go from Here?

After diagnostic analyses on the amount and type of missing data, as we did in the present work, the question arises about how to handle missing data in subsequent analyses. Several methods, from classic to newer options, have been proposed in the literature (e.g., Graham, 2009; Young & Johnson, 2013). Listwise deletion is still the most frequently used, but it determines a loss in sample size and, in the case of MAR or NMAR, can lead to biased estimates. Non-response in a family dataset may have at least two consequences if it is handled with listwise deletion: bias and error. The first consequence is that biases may occur in descriptive statistics and estimated parameters. Estimation bias is due to the fact that analyses are conducted on a different population from the target population selected, so external validity problems occur (Newman, 2014). The second consequence is error of inference in hypothesis testing (both type I and II) due to inaccurate standard errors (Graham, 2009). Thus, traditional methods for handling missing data (e.g., listwise deletion, mean substitution, etc.) have been subject to much criticism and are generally not recommended, while newer analytical tools (e.g., multiple imputation; maximum likelihood) are highly recommended, though rarely applied to family research (see, for exceptions, Donato et al., 2014; Kazak et al., 2004; Sassler & McNally, 2003). In particular, only a few studies (Kalmijn & Liefbroer, 2011; Young & Johnson, 2013) focused on what methods are the most useful with "secondary respondent" missing data. In an effort to accompany family researchers in these further steps of missing data management, a user-friendly step-by-step guide taking into account the different types of missingness described here is forthcoming.

NOTES

1. Similarly, missingness can also be found at the construct level, which means that all the items measuring a specific construct are missing for one or more respondents. In this paper, we will focus only on item level missingness for parsimony. Indeed, theory and method related to the item missingness can be applied to construct level missingness as well.
2. Some authors, in fact, consider MCAR a special case of MAR in which missingness does not depend on unobserved or on observed data (Schafer & Graham, 2002).
3. The term MAR has been criticized because in this case data are not randomly missing, at least not completely (e.g., Graham, 2009). They are randomly missing *once controlled for the variable explaining the missingness*. We used this term because it is deep-seated and ubiquitous in the literature on missing data analysis.
4. For diagnostic purposes, dummy variables can be computed at any of the levels described previously. For the purpose of identifying auxiliary variables to be used in missing data management procedures (FIML or MI), dummy variables are usually computed at the item or construct levels.
5. The other self-report instruments referred to the following individual constructs: self-efficacy, sense of coherence. Further instruments were used to assess the following relational constructs: relational support, conflict, differentiation, commitment, relational influence. Finally, sociodemographic variables referred to: gender, education, number of family members, number of family members earning money, income. The complete list of measures is available from the authors upon request.
6. The other self-report instruments referred to the following individual constructs: generativity, depression, size of social network, social support, religiosity, religious practice, quality of relationship with premarital partners, own health conditions, health conditions of one's parents. Further instruments were used to assess the following relational constructs: intimacy, passion, commitment, dyadic forgiveness, dyadic coping, inclusion of the other in the self. Finally sociodemographic variables referred to: age, civil status, years married, number of children, income, gender of primary respondent's child, education, household. The complete list of measures is available from the authors upon request.

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