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THE ROLE OF INDIVIDUALS' AND THEIR PARTNERS' POSITIVITY IN THE SATISFACTION WITH THE RELATIONSHIP: AN ACTOR-PARTNER INTERDEPENDENCE MEDIATION MODEL

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Over the last thirty years, the actor-partner interdependence model (Kenny, 1996) became an important methodology to address interpersonal perceptions in dyads. In this contribution, we present each practical step to conduct an extended version of it, the actor-partner interdependence mediation model (Ledermann, Macho, & Kenny, 2011) using multilevel modeling. Specifically, we posit that individuals' and their romantic partners' positivity, a personality disposition, enhance relationship satisfaction, through the individuals' perceptions of partners' positivity. Results from 161 heterosexual couples confirmed that both actor and partner's positivity predicted satisfaction directly and indirectly, through the actor's perception of partner's positivity. Therefore, importantly, in the observed relationships, the mediating role of the individuals' perception of their partners confirmed the theoretical assumptions of the interpersonal perception framework. The innovative contribution of this work lays, in actual fact, in the possibility offered by the model proposed to include this latter variable as a mediator.

Keywords: APIMeM; Mediation; Interpersonal perception; Positivity; Relationship satisfaction.

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In recent years, the study of social relationships has led to growing research of multifaced computational models to reflect social phenomena of even more complex nature. Of particular interest was the development of models that could account for information coming from different persons (i.e., informants). These models rest on the idea that social, but also individual, variables are strongly influenced by one's relationships with others. Among different statistical frameworks, the actor-partner interdependence model (APIM; Kenny, 1996, 2018) has rapidly reached high popularity. In its simplest declination, it allows accounting for the effect of a predictor (measured in two members of a dyad, or even in an individual and its group) on an outcome variable (individual or social).

Overall, the APIM is a model able to answer a high number of theoretical questions linked to social relationships across different psychological fields (Kenny, 2018). Likely, its high versatility contributed to the model's popularity. One of the most important features attributable to the APIM is the ability to control for nonindependence among dyadic sets of observations that is the shared variance derived by data coming from different sources (Kenny, Kashy, & Cook, 2006; Kenny, Mannetti, Pierro, Livi, & Kashy, 2002). Nonindependence refers to the fact that scores of two individuals that are in a significant relationship (e.g., romantic partners, roommates, friends) are more similar than scores observed between two other random persons. This is so precisely by virtue of the unique relationship that exists between them (Kenny, 1996).

Within this frame of reference, of particular importance are some extensions of the model that proliferated over the past decades that helped to deepen the understanding of dyadic and even group relationships (e.g., the group actor-partner interdependent model; Kenny & Garcia, 2012). In this regard, the actor-partner interdependence mediation model (APIMeM; Ledermann, Macho, & Kenny, 2011) revealed fundamental in shedding light on the specific interpersonal mechanism that underly the relationship between two individuals. Basically, this model extends the APIM to a third (dyadic) variable, namely a mediator, through which both individuals' variables exert an effect on the outcome.

Over the years, researchers approached APIMeM using both multilevel modeling (MLM) and structural equation modeling (SEM), mostly depending on the distinguishability of the dyads (Ledermann & Kenny, 2017). Distinguishability refers to the possibility to attribute to both members of the dyad a specific characteristic or role in the relationship (e.g., female and male partner in heterosexual couples, supervisor and collaborator in the case of a couple of colleagues) as opposed to dyads where members are theoretically exchangeable (e.g., homosexual couples, two roommates, or two friends). In this contribution, we will make use of the APIMeM with MLM. For demonstration purposes, we specifically choose to test our assumptions on empirically indistinguishable dyads, as it constitutes the most convenient case to use MLM for computing an APIMeM (Ledermann & Kenny, 2017; Olsen & Kenny, 2006).

The General Formulation for the APIMeM Indistinguishable

In this section, we would give the general formulation of the APIMeM with indistinguishable dyads. We will start with the general formulation of the distinguishable case. In the most classical APIM distinguishable, there is one predictor measured in both members of the dyad. The first focal individual is called *actor* and the second individual is the *partner*. Consider the most common case in which the outcome variable Y is an individual outcome, meaning that it can vary at both between and within-dyads levels (i.e., thus, it constitutes a mixed variable, see Kenny et al., 2006). The effect that the actor predictor variable X_A exerts on the actor outcome variable Y_A and the effect that the partner predictor variable X_P exerts on the partner outcome variable $Y_{P,}$ both controlling for the effect of the other member, are called *actor effects*; whereas, the effect of X_P on Y_A and that of X_A on Y_P, both controlling for the actor effects, are called *partner effects*. Predictor variables are correlated, as well as the residuals of Y_A and Y_P.

The case of indistinguishability is different. For indistinguishability, we mean that actor and partner effects are estimated to be the same across the two members of the dyad (Kenny et al., 2006). This could be so for two reasons: (1) a theoretical reason, the two members are not distinguishable on any characteristic or role that could justify two different effects; (2) an empirical reason, a dyad that theoretically could show distinguishable effects, where however distinguishability did not subsist empirically (Kenny, 1996; Kenny et al., 2006). In APIM and APIMeM indistinguishable, the two members of the dyads are substantially interchangeable.

In the case of APIMeM indistinguishable with MLM, each step of the mediation is estimated separately. In the classical mediation analysis, there are three focal models (Baron & Kenny, 1986): the first tests the effect of the predictor X on outcome Y (first step), the second gives the estimation of the mediator M from X (second step), the third is the estimation of Y from both M (third step) and X (fourth step). Consequently, the total effect *c* of X on Y is the effect when X is alone in the model and is also the sum of the indirect effect and the direct effect. The indirect effect of X on Y through M is the product of the effects a (X on M) and b (M on Y); whereas, the direct effect c' is the effect of X on Y controlling for M. In APIMeM, there are total, indirect, and direct effects for each member of the couple. In Figure 1, there is a graphical presentation of the overall model. The general formulation is:

$$Y_A = i_{YA}+c_1X_A+c_3X_P+e_Y \quad (1)$$

$$Y_P = i_{YP}+c_2X_A+c_4X_P+e_Y \quad (2)$$

$$M_A = i_{MA}+a_1X_A+a_3X_P+e_M \quad (3)$$

$$M_P = i_{MP}+a_2X_A+a_4X_P+e_M \quad (4)$$

$$Y_A = i_{YA}+c'_1X_A+c'_3X_P+b_1M_A+b_3M_P+e_y \quad (5)$$

$$Y_P = i_{YP}+c'_2X_A+c'_4X_P+b_2M_A+b_4M_P+e_y \quad (6)$$

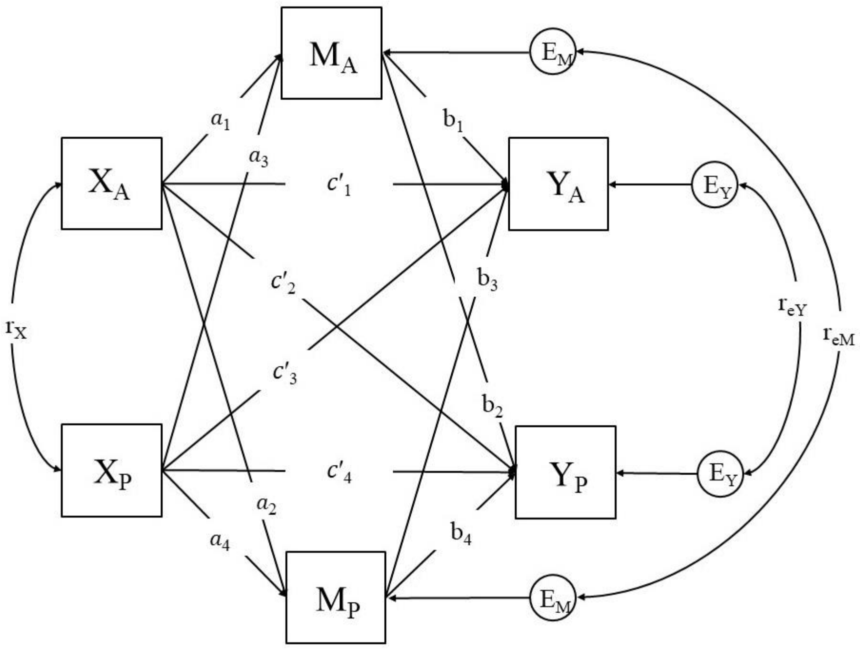

FIGURE 1
The APIMeM.

Note. Parameters a refer to the effects of the predictors on the mediators, parameters b refer to the effects of the mediators on the outcome variables and, lastly, parameters c' are generally referring to direct effects. Total effects c are $c_1 = c'_1 + a_1b_1 + a_2b_3$, $c_2 = c'_2 + a_1b_2 + a_2b_4$, $c_3 = c'_3 + a_3b_1 + a_4b_3$, and $c_4 = c'_4 + a_3b_2 + a_4b_4$. Note that in the indistinghuishable case the following constrains should be applied: $a_1 = a_4$, $a_3 = a_2$, $b_1 = b_4$, $b_3 = b_2$, $a_1b_1 = a_4b_4$, $a_2b_3 = a_3b_2$, $a_1b_2 = a_4b_3$, $a_2b_4 = a_3b_1$, $c'_1 = c'_4$, $c'_3 = c'_2$, $c_1 = c_4$, and $c_2 = c_3$.

Equations 1 and 2 correspond to the first step of the mediation, Equations 3 and 4 to the second step, Equations 5 and 6 to the third and fourth step. The total actor effects are c_1 in Equation 1 and c_4 in Equation 2, whereas total partner effects are c_3 in Equation 1 and c_2 in Equation 2. In Equations 3 and 4, weights a_1 and a_3 are respectively actor and partner effects on M_A, and a_2 and a_4 are partner and actor effects on M_P. In the indistinguishable case, $a_1 = a_4$ and $a_3 = a_2$. In Equations 5 and 6, weights b_1 and b_3 are respectively actor and partner effects on Y_A through M_A and M_P, and b_2 and b_4 are partner and actor effects on Y_P through M_A and M_P. In the indistinguishable case, $b_1 = b_4$ and $b_3 = b_2$. Moreover, the actor indirect effects, namely the effects of X_A on Y_A through M_A, are a_1b_1 and a_4b_4, which in the indistinguishable case are equal and, through M_P, they are a_2b_3 and a_3b_2 which are equal as well. The partner indirect effects, namely the effects of X_A on Y_P through M_A, are a_1b_2 and a_4b_3, which are equal and, through M_P, a_2b_4 and a_3b_1, which are equal as well. The direct effects are then c'_1, c'_2, c'_3, and c'_4. Specifically, c'_1 and c'_4 are actor direct effects and are equal in the case of indistinguishable dyads; likewise, c'_3 and c'_2 are partner direct effects and are equal. The total effects c_1, c_2, c_3, and c_4 are given by the sum of the direct and indirect effects as follows:

$$c_1 = c'_1+a_1b_1+a_2b_3 \tag{7}$$

$$c_2 = c'_2+a_1b_2+a_2b_4 \tag{8}$$

$$c_3 = c'_3+a_3b_1+a_4b_3 \tag{9}$$

$$c_4 = c'_4+a_3b_2+a_4b_4 \tag{10}$$

In the case of indistinguishable dyads, $c_1 = c_4$ and $c_2 = c_3$. In sum, in an indistinguishable APIMeM, variances, intercepts, effects, and means, are set to be equal across both members of the dyad. Therefore, one should note here that, in estimating such a model, SEM would require a high number of equality constraints to be imposed on variances, actor and partner effects, intercepts, and means. For instance, Ledermann and Kenny (2017) estimate a total of 96 constraints for an APIMeM indistinguishable with four variables and three covariates. Thus, although SEM gives the possibility to estimate the models in one run, MLM has been considered a better choice in the case for APIMeM indistinguishable (Ledermann & Kenny, 2017; Olsen & Kenny, 2006). Before giving an empirical test of the model, in the next section, we will introduce our theoretical assumptions regarding positivity and relationship satisfaction.

THE CASE OF POSITIVITY AND RELATIONSHIP SATISFACTION

Satisfying and fulfilling romantic relationships are the cornerstone of social life and an important pathway to mental and physical well-being as well as happiness in the long term (Braithwaite, Delevi, & Fincham, 2010; Dush & Amato, 2005; Kiecolt-Glaser & Newton, 2001). Among the relevant predictors of satisfaction, studies on the role of personality of both partners in the relationship satisfaction have a long research history (Cooper & Sheldon, 2002; Dyrenforth, Kashy, Donnellan, & Lucas, 2010; Malouff, Thorsteinsson, Schutte, Bhullar, & Rooke, 2010). In a recent review (Weidmann, Ledermann, & Grob, 2016), studies were confronted. Unsurprisingly, neuroticism negatively predicted relationship satisfaction, whereas agreeableness and conscientiousness revealed positive predictors of relationship satisfaction. However, as it was pointed out by the authors, only little of the variance is explained by these three traits (Weidmann et al., 2016).

Other studies demonstrated the relevance of additional personality traits, such as partners' optimism (Assad, Donnellan, & Conger, 2007; Srivastava, McGonigal, Richards, Butler, & Gross, 2006) and self-esteem (Sciangula & Morry, 2009) for the prediction of relationship satisfaction. In this contribution, we seek to explain how positivity personality trait, defined as a stable disposition to have a positive view of oneself, life, and future, and composed of three latent factors that are, self-esteem, life satisfaction, and optimism (Caprara et al., 2009), relates to relationship satisfaction. Individuals high in positivity are characterized by a relatively stable global disposition to see events as favorable and to have more fulfilling lives (Theodorou, Violani, & Alessandri, 2017). From a theoretical point of view, the construct of positivity shares similarities to other relevant constructs related to well-being as the sense of coherence (Antonovsky, 1979), and has been previously theorized by important theoretical accounts of individuals' motivation, such as Hobfoll's (1989) conservation of resources theory.

Previous studies have extensively demonstrated how positivity sustains the development of successful social relationships and promotes social adaptation (Caprara, Alessandri, & Caprara, 2019; Livi, Theodorou, Rullo, Cinque, & Alessandri, 2018). In particular, research showed how not only individual-level positivity but also positivity of the others involved in the same social context has beneficial effects on the individual social adjustment and success (Livi, Alessandri, Caprara, & Pierro, 2015; Theodorou, Livi, Alessandri, Pierro, & Caprara, 2019). In line with these findings and with classical personality APIMs (see Figure 2), we predict that actor and partner's positivity would positively predict relationship satisfaction:

H1: Actor's positivity positively predicts actor's relationship satisfaction, controlling for partner's positivity.

H2: Partner's positivity positively predicts actor's relationship satisfaction, controlling for actor's positivity.

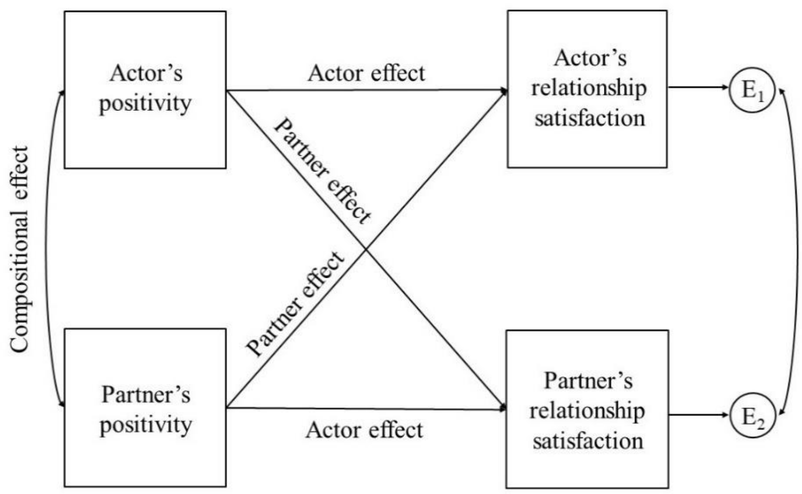

FIGURE 2
The conceptual personality model.

The research found that not only the personality of the two partners is important, but also how partners see each other (i.e., the interpersonal perception) is central in determining relationship satisfaction (Kenny & Acitelli, 2001; Weidmann et al., 2016). In fact, perceptions can predict both partners' behavior in the long term. For instance, negative expectations about the other partner can drive overreactions from both sides that, in turn, can predict breakups (Downey, Freitas, Michaelis, & Khouri, 1998). Perceptions directly intervene in shaping partners' behaviors also in what has been called the Michelangelo phenomenon (Drigotas, Rusbult, Wieselquist, & Whitton, 1999). Specifically, this phenomenon demonstrates how, similarly to the Michelangelo's belief that carving a sculpture was nothing but bringing to light the real essence of the work hidden under a piece of marble, partner's expectations help the individual to unveil their own ideal self and move toward it. This mutual tendency constantly pushes the other to grow and improve oneself, which leads, ultimately, in an enhancement of couple well-being (Rusbult, Kumashiro, Kubacka, & Finkel, 2009).

Studies that used accuracy-bias models (Kenny & Acitelli, 2001), where the outcome is the perception that the actor has of his or her partner's characteristic (see Figure 3), revealed how partners can definitely be able to see the significant other in a clear way (accuracy), and still forge a different perception of the him/her (bias). Indeed, the other in the relationship is very important for one's identity as the partner becomes a part of the self (Aron, Aron, Tudor, & Nelson, 1991). Therefore, partners are motivated to see the other as they may need to see them (Gagné & Lydon, 2004). In fact, having a specific reference image in mind allows controlling the other and having a favorable view of the relationship. Thus, usually, partners see others as more similar to their own as they really are (Gagné & Lydon, 2004; Kenny & Acitelli, 2001).

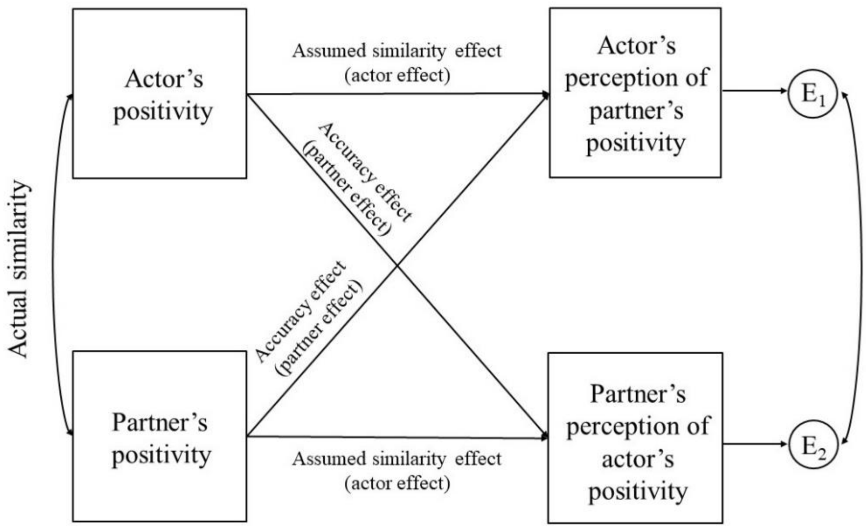

FIGURE 3
The conceptual accuracy-bias model.

The need to predict the partner's behavior leads individuals to refer constantly to the real characteristic of the partner. This may seem a paradox, however, perceivers cannot have a distort perception if they do not know how the object of perception really is (Fletcher, 2015; Gagné & Lydon, 2004). Therefore, although independent, accuracy and bias co-exist and have both been shown to predict relationship satisfaction (Fletcher, 2015). Accordingly, we expect to find significant and positive effects of both actor's positivity (i.e., bias or assumed similarity effect) and partner's positivity (i.e., accuracy effect) on actor's perception of partner's positivity. In turn, higher bias and accuracy effects are expected to result in greater relationship satisfaction. Accordingly:

H3: A higher bias effect results in greater relationship satisfaction. More specifically, the positive effect of actor's positivity on actor's relationship satisfaction would be mediated by higher actor's perception of partner's positivity.

H4: A higher accuracy effect results in greater relationship satisfaction. More specifically, the positive effect of partner's positivity on actor's relationship satisfaction would be mediated by higher actor's perception of partner's positivity.

In the literature, an effect of the length of the relationship on both bias and accuracy is reported (Kenny & Acitelli, 2001). Often, higher relationship length corresponds to higher accuracy in the perception (Fletcher & Kerr, 2010; Sillars, Pike, Jones, & Murphy, 1984). Basically, this would be so because of a longer acquaintance between the partner and ample time to know him or her well. Nevertheless, some studies report that higher length is associated with lower accuracy (Fletcher & Kerr, 2010; Kilpatrick, Bissonnette, & Rusbult, 2002). This result was explained referring to a sort of cognitive economy partners would engage in. Specifically, it was argued that, in the long run, partners may feel overconfident about their knowledge of the partner and, consequently, avoid updating the partner's image over time. Although the effect of this variable in previous studies is not straightforward, we decided to account for it in our model.

Another source of bias in couple's perceptions is constituted by what has been called positive illusions, referring to the motivation to see the partners more optimistically, deviating from how they really are (Murray, Holmes, & Griffin, 1996). These positive illusions seem to sustain the gratification resulting from the relationship and to facilitate endurance in the long run (Gagné & Lydon, 2004). In this regard, we assume that positivity is a desirable trait and consequently hypothesize that there should be a positive bias in the perception of partner's positivity (Rusbult, Van Lange, Wildschut, Yovetich, & Verette, 2000; West & Kenny, 2011). Specifically, partners would tend to see the other in a positive light, in this case, with higher levels of positivity.

H5: There is a positive bias in assessing partner's positivity.

Description of the Database

We will test our assumptions on a database consisting of a convenience sample of 161 heterosexual couples (322 participants) that filled out a questionnaire including measures of positivity and satisfaction with the relationship. Participants' age ranges from 17 to 72 with an average of 31.45 (*SD* = 12.65), whereas length of the relationship varies from 2 months to 54 years, with an average of 117.63 months (*SD* = 137.50). Of the total sample, 91 couples (56.5%) were dating, 23 (14.3%) were living together, 45 (28%) were married, and 2 (1.2%) did not respond to this question. Since gender was coded 1 for male and 2 for female, the focal member of the dyad or actor is the male partner.

Measures

Positivity. Positivity was assessed using the P-scale (Caprara et al., 2012), an instrument composed of eight items (e.g., "I am satisfied with my life" and "I generally feel confident in myself"), one of them being reverse-scored (i.e., "At times, the future seems unclear to me"). Responses range from 1 (*strongly disagree*) to 5 (*strongly agree*). The Cronbach's alpha is .87 for both males and females.

Perceptions of partner's positivity. Perceptions of partner positivity was measured using the P-scale, revised to ask about partner's positivity. Examples of items are: "My partner is satisfied with his/her life," and "My partner generally feels confident in himself/herself." Responses range from 1 (*strongly disagree*) to 5 (*strongly agree*). In the present study, the Cronbach's alpha is .85 for males and .87 for females.

Satisfaction with the relationship. The satisfaction with the relationship was measured using 17 adjectives and participants were invited to evaluate how well each one of them describes their relationship with their partner, from 1 (*Slightly*) to 7 (*Extremely*). Specifically, eight adjectives were negative (e.g., "boring") and nine were positive (e.g., "satisfying"). Negative adjectives were then reverse-coded and a mean of the scores was computed; thus, higher scores indicate higher relationship satisfaction. The Cronbach's alpha is .90 for males and .91 for females.

Positivity, perceptions of the other partner's positivity, and satisfaction with the relationship varied at both within- and between-dyads levels, so they were mixed variables (Kenny, 1988; Kenny et al., 2006). As for the covariate, namely length of the relationship, it was computed as the mean value of the length of the relationship in months reported by both partners. This means that this variable varied only between-dyads (Kenny, 1988; Kenny et al., 2006). There were no missing values.

The means, standard deviations, and correlation among variables of the study are reported in Table 1. Regarding the correlation matrix, it is worth noting that the accuracy correlations (i.e., the correlation between the perception of the partner's characteristic and the partner's self-reported measure) were .52, p < .01 for males, and .59, p <. 01 for females. Moreover, the actual similarity correlation (i.e., the correlation between self-reported measures of the actor and the partner) was significant and equal to .27, p < .01, indicating a compositional effect. It refers to the very prerogative that leads to a certain relationship between two individuals, which is that they are usually more similar than two other persons (Kenny, 1996). The outcome variables from both members are positively and significantly correlated, .52, p <. 01, indicating that the individual level of satisfaction is strictly related to the satisfaction of the other partner. Lastly, the length of the relationship is negatively and significantly related to the satisfaction of both partners: for males −.19, p < .05, and for females −.36, p < .01, indicating that the lower the longevity of the couple the higher the level of satisfaction reported by each partner.

TABLE 1
Means, standard deviations, and correlation among study variables

	M	*SD*	1	2	3	4	5	6	7
1. POS_A (M)	3.69	0.85	-						
2. POS_{AP} (M)	3.58	0.77	$.46^{**}$	-					
3. SAT_A (M)	5.92	0.68	$.43^{**}$	$.38^{**}$	-				
4. POS_P (F)	3.55	0.85	$.27^{**}$	$.52^{**}$	$.30^{**}$	-			
5. POS_{PA} (F)	3.53	0.85	$.59^{**}$	$.21^{**}$	$.29^{**}$	$.36^{**}$	-		
6. SAT_P (F)	5.84	0.81	$.18^{*}$	$.17^{*}$	$.52^{**}$	$.40^{**}$	$.33^{**}$	-	
7. Length of the relationship (months)	117.63	137.72	−.07	.04	$-.19^{*}$	.04	−.11	$-.36^{**}$	-

Note. POS_A = actor's positivity; POS_P = partner's positivity; SAT_A = actor's relationship satisfaction; SAT_P = partner's relationship satisfaction; POS_{AP} = actor's perception of partner's positivity; POS_{PA} = partner's perception of actor's positivity; M = male partner; F = female partner.
$^{**}p$ <.01. $^{*}p$ < .05.

ESTIMATION OF THE APIMEM: PRACTICAL STEPS

In this section, we will describe in detail each step for conducting an APIMeM indistinguishable with MLM. For each of the consequential actions, we would give theoretical and practical recommendations. The reader may refer for each step to the related R code in the Appendix. For all the analyses, we would make use of the R package dyadr (Garcia, Kenny, & Madziwo, 2019). This package presents some unique functions that have been developed to specifically address the use of APIMeM with MLM. For additional information, codes, and other practical issues the reader can refer to the GitHub webpage of the package (Garcia, 2019) and to David Kenny's webpage DyadR (Kenny, 2019). After having established that our data follow a multivariate normality, all models were estimated using maximum likelihood (ML) estimation.

Step 1. Preliminary Actions: Management of the Database

One important action to take before the beginning of the investigation refers to the management of the database. To our purposes, we need to get at least two kinds of datasets. The first one is an individual database, where each individual's variables are on one row. This database will serve to get descriptive statistics at the individual level. We may also need a dyadic database, meaning a database where each dyad is on a row, to get the descriptive statistics and correlations of each variable different for actors and partners.

Then, for computing our models with dyadr, we will need a pairwise database, which is a specific database that shares some advantages of both dyadic and individual databases. Similar to the individual database, in this kind of database, each row presents an individual's variables. In addition, each row presents also its partner variables, remarking the dyadic database. Thus, in each column, the actor's variables as well as the partner's variables are computed separately but include both partners' scores. This is the reason that makes this database inappropriate to use it for other purposes apart from the estimation of the model (for a more detailed description of the characteristics of each database the reader can refer to Kenny et al., 2006). For our study, we obtained a pairwise database using the online app developed by Kenny (2017).

Step 2. Computing the Pearson's Intraclass Correlation Coefficient (ICC)

The ICC gives back the extent to which both partners' outcomes are interdependent (Kenny et al., 2006, 2002). Although the APIMeM (as for the APIM) relies on the assumption of nonindependence, it is recommended to compute the ICC for each variable to empirically test this theoretical assumption. As it is a prerogative of the model, this should be done before estimating the model. For doing so, the syntax comprises the specific function that gives back the Pearson's ICC specifying both actor and partner's variables.

In our database, for actor's and partner's positivity, the Pearson's ICC is .26, $p < .001$; for the proposed moderator, namely perceptions of the other partner's positivity, the ICC is .20, $p < .001$; lastly, for the final outcome, namely relationship satisfaction of both partners, the ICC is .50, $p < .001$. On the whole, these results indicate that variables are moderately-low correlated, confirming our assumptions of nonindependence. In particular, the first one has been attributed to the above mentioned compositional effect; whereas the second one can be attributed to mutual influence (i.e., the fact that partners influence each other), and the third one to mutual influence and common fate (i.e., partners and their relationship are exposed to the same factors that can influence them; Kenny, 1996).

Step 3. Excluding Moderation

Before testing the mediation model, it is essential to assure that the proposed mediator does not interact with the two predictors in predicting the outcome, namely that it is not in actual fact a moderator of the relationship hypothesized (Baron & Kenny, 1986). To do so, we will test two different models, one with distinguishable and one with indistinguishable moderation effects, and we will compare them to the analogous models without the interaction terms (Garcia, Kenny, & Ledermann, 2015). Following our reasoning, we would be able to test if there are any distinguishable (first comparison) or indistinguishable (second comparison) moderation effects. Please note that it is beyond the scope of this step to test distinguishability, to which it is dedicated the next step. We run four different models: (1) a model in which the moderation effects are in interaction with gender (testing moderation distinguishable); (2) a distinguishable model without moderation effects; (3) a model in which the moderation effects are indistinguishable; (4) an indistinguishable model without moderation effects. In the distinguishable models, the variable gender is in interactions with all the other effects (i.e., as in an "interaction APIM"; Ledermann & Kenny, 2017). Then, we will look at the results of omnibus tests conducted on each pair of models, from the less to the more conservative (Kenny et al., 2006).

In practice, to our purposes, in the first model the variable relationship satisfaction is predicted by the two predictors, the two mediators, and all the possible interaction combination among them and the variable gender. In the second model, the moderation effects are omitted, and gender is the only variable that interact with the predictors. In the third model, we have the predictors and the moderation effects, whereas in the fourth model we have only the predictors' effects. The covariate length of the relationship is included in all the estimated models. Results of the two likelihood ratio tests (LRT) are reported in Table 2, along with the AIC, BIC, and −2 log likelihood indices and attest that the best fitting model is the less conservative one, where no moderation effects are included. These findings exclude that perception of partner's positivity can be a moderator of the relationship investigated; hence, we can move on with the rest of the analyses.

TABLE 2
Results of the omnibus tests conducted in order to test moderation

	df	AIC	BIC	−2 log likelihood	Likelihood ratio test	*p* value
Model 1	22	615.84	698.88	−285.92		
Model 2	14	608.41	661.26	−290.21	8.57	.38
Model 3	12	608.38	653.68	−292.19		
Model 4	8	603.51	633.71	−293.75	3.13	.54

Note. Model 1 = a model including moderation effects distinguishable by gender; Model 2 = a distinguishable model without moderation effects; Model 3 = a model including moderation effects indistinguishable by gender; Model 4 = an indistinguishable model without moderation effects. All the estimated models included the length of the relationship as covariate. Likelihood ratio tests are conducted between the first two and the last two models.

Step 4. Test for Distinguishability

The next step is to test whether the observed effects for mediation are distinguishable by gender, namely between the male and female partners (Kenny & Acitelli, 2001; Kenny et al., 2006). Note that in the previous step, we established that there are not any distinguishable or indistinguishable moderation effects. Here, on the other hand, we test distinguishability for each of the three models for mediation outlined by Baron and Kenny (1986). The first model tests the first step of mediation, namely the total effect c of both actor and partner variables (controlling for each other) on the outcome. The second model corresponds to the second step, the estimation of the a path, meaning the effect of both actor and partner variables on the mediator. The third model allows the test of both Step 3, the b path from the mediator to the outcome, and Step 4, the direct effect c' of the two actor and partner variables controlling for the mediator.

Then, in order to test for distinguishability, we run each model treating effects both as distinguishable and indistinguishable, with a total of six models to compute. In the case of the models with distinguishable effects, we compute an "interaction APIM" (Ledermann & Kenny, 2017), namely the gender variable is inserted and posed in interaction with the other variables. Then, we apply an omnibus test for distinguishability (Kenny et al., 2006) in which we compare each model with a very similar one in which effects are posed to be different by sex.

Although we already knew that our dyads are indistinguishable, for illustrative purposes, we will give an example of a test for distinguishability. We run each model including the length of the relationship. Unsurprisingly, results revealed that the effects were indistinguishable for Model 1 (LRT = 6.67, p = .15), for Model 2 (LRT = 5.87, p = .21), and for Model 3 (LRT = 7.10, p = .31). Therefore, we can put aside the null hypothesis for which the less conservative model adds substantial value to the more conservative one and precede treating dyads as indistinguishable (Kenny et al., 2006).

Step 5. Estimating the APIMeM indistinguishable

In getting the complete model, we will describe five practical steps as follows.

a. Standardization of variables. To get standardized estimates, we must standardize all variables before being included in the analysis (Ledermann & Kenny, 2017).

b. The four steps. In this stage, to test the four steps of the mediation, we launch each of the three models mentioned above using the standardized variables.

c. Obtaining the R squared. The R squared for each model is obtained comparing the standard deviation of errors for each model to the standard deviation of errors of an empty model (Kenny et al., 2006).

d. Getting the partial ICC. The partial ICC indicates how much of the shared variance between the two partners' outcomes remained unexplained after including the model's predictors (Kenny & Kashy, 2010; Kenny et al., 2006).

e. Indirect effects. We can get indirect effects using a simple multiplication between paths. In APIMeM with indistinguishable dyads, there are a total of four indirect effects: two actor indirect effects, namely the effect of the individual predictor variable on his/her outcome through his/her mediator and through the other member's mediator; two partner indirect effect, namely the effect of the individual's variable on the other individual's variable through his/her mediator and through the other individual's mediator. To test the statistical significance of the indirect effects, the best strategy is using the Monte Carlo method based on a parametric bootstrap procedure that gives back confidence intervals and p values (Ledermann & Kenny, 2017; Selig & Preacher, 2008).

Moving to apply these steps to our example, we proceed testing the four steps of the mediation analysis mentioned above. In Model 1, we test the total effect of actor and partner's positivity on satisfaction with the relationship. To this aim, we pose (1) actor's positivity, (2) partner's positivity, and (3) length of the relationship on satisfaction with the relationship as the outcome. Results attested positive and significant total effects of both actor and partner's positivity on satisfaction with the relationship (standardized regression coefficients were respectively B = .38 and B = .13, see Table 3, first column). These findings, confirming respectively H1 and H2, indicate that the higher both partners' positivity, the greater the actor's relationship satisfaction.

Of interest, the effect of the length of the relationship was negative and significant, revealing that the higher the length of the relationship the lower the satisfaction ($B = -.27$). The R^2 was equal to .26, and, therefore, we can conclude that this model explained 26% of the outcome variance. The partial ICC, namely the correlation between the two partners' satisfaction controlling for the effect of the predictors and the

TABLE 3
Results of the APIMeM

	Relationship satisfaction						Actor's perception of partner's POS		
	Model 1			Model 3			Model 2		
	B	*SE*	95% CI	*B*	*SE*	95% CI	*B*	*SE*	95% CI
Intercept	.01	.06	[−.11, .11]	.01	.06	[−.11, .11]	.01	.04	[−.08, .08]
POS_A	$.38^{***}$	.05	[.28, .47]	$.34^{***}$	.06	[.21, .47]	$.28^{***}$	.05	[.19, .37]
POS_P	$.13^{**}$	.05	[.03, .22]	.05	.06	[−.08, 18]	$.48^{***}$	.05	[.39, .57]
POS_{AP}	-	-	-	$.18^{**}$	.07	[.05, .31]	-	-	-
POS_{PA}	-	-	-	−.03	.07	[−.16, .10]	-	-	-
Length of the relationship	$−.27^{***}$	.06	[−.39, −.16]	$−.27^{***}$	.06	[−.38, −.16]	−.03	.04	[−.11, .04]
−2 log likelihood	−394.43			−387.37			−373.89		

Note. POS_A = actor's positivity; POS_P = partner's positivity; SAT_A = actor's relationship satisfaction; SAT_P = partner's relationship satisfaction; POS_{AP} = actor's perception of partner's positivity; POS_{PA} = partner's perception of actor's positivity.
$^{***}p < .001$. $^{**}p < .01$.

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covariate, was equal to .39, indicating a high degree of unexplained interdependence even controlling for our predictors.

In Model 2, we then move to test the first path of the mediation analysis, namely the effect of actor and partners' positivity on the perception of partner's positivity. Therefore, we compute a model in which we pose individual positivity and partner's positivity as predictors and the actor's perception of partner's positivity as the outcome. Again, we include the covariate length of the relationship in the model. The results of this model are shown in Table 3, third column, and revealed a positive and significant effect of actor's positivity, $B = .28$, and a positive and significant effect of partner's positivity, $B = .48$. The effect of the length of the relationship was, instead, nonsignificant, $B = -.03$. Importantly, the R^2 was equal to .38; thus, this model explained 38% of the outcome variance. The partial ICC was equal to −.24.

In Model 3, we tested both Steps 3 and 4 of the mediation: the former refers to the second path of the mediation model that is the effect that the actor's perception of partner's positivity has on satisfaction with the relationship; the latter is the direct effect, that is, the unexplained effect of the predictors, in this case, the effect of actor's and partner's positivity on the outcome satisfaction with the relationship, controlling for the mediator (i.e., actor's perception of partner's positivity). Thus, we pose actor and partner's positivity, actor's perception of partner's positivity, and partner's perception of actor's positivity on satisfaction with the relationship. Lastly, the covariate length of the relationship is included in the model as well.

Results of this latter model are showed in Table 3, second column, and attest: a positive and significant effect of actor's perception of partner's positivity ($B = .18$); a nonsignificant effect of partner's perception of actor's positivity ($B = -.03$); a positive and significant effect of actor's positivity ($B = .34$); a nonsignificant effect of partner's positivity ($B = .05$); and a significant effect of length of the relationship ($B = -.27$). The model's R^2 was .29; therefore, the model explained 29% of the outcome variance. The partial ICC was equal to .42, indicating again a high nonindependence in the scores of satisfaction reported by the two partners when controlling for all the model's predictors.

To verify our predictions regarding the indirect effects, we test the effect that both actor's and partner's positivity have on the actor's relationship satisfaction through the perception of partner's positivity. In this study, we obtain 95% confidence intervals (CI) with 10,000 runs. As expected, actor's positivity revealed a significant indirect effect on his/her relationship satisfaction through his/her perception of partner's positivity — actor indirect effect: .05, $p < .01$, 95% CI [0.01, 0.09]. In particular, this effect was equal to 8% of the total effect and confirmed H3, by which the higher the bias the greater the relationship satisfaction. Moreover, partners' positivity, which did not have a significant direct effect on satisfaction, showed, importantly, an indirect effect on actor's relationship satisfaction through the actor's perception of partner's positivity — partner indirect effect: .09, $p < .01$, 95% CI [0.02, 0.15]. Of interest, this effect was equal to 50% of the total effect, a relevant part of the total effect, and ultimately confirmed H4, suggesting that the higher the accuracy the greater the relationship satisfaction.

Interestingly, the other two indirect effects were nonsignificant, namely the partner indirect effect of actor's positivity on partner's relationship satisfaction through the actor's perception of partner's positivity — indirect effect: −.01, $p = .62$, 95% CI [−0.05, 0.03] — suggesting that being biased does not predict the other partner's relationship satisfaction, and the actor indirect effect of partner's positivity on partner's relationship satisfaction through the actor's perception of partner's positivity — indirect effect: −0.02, $p = .62$, 95% CI [−0.08, 0.05] — attesting that being accurate does not predict the other partner's relationship satisfaction.

Step 6. Getting the Figure

To our knowledge, there are no apps that are capable of returning the graphical results of the APIMeM with MLM. Thus, we offer a few indications to get an understandable figure. Contrary to APIMeM with SEM, where model's estimates are obtained at once, as we saw above, using MLM we have to test three models separately. Consequently, in preparing a figure, we should acknowledge that the results are coming from three different models. As for the APIM, in the case of indistinguishable dyads, the figure is specular. See Figure 4 for a graphical representation of our example model.

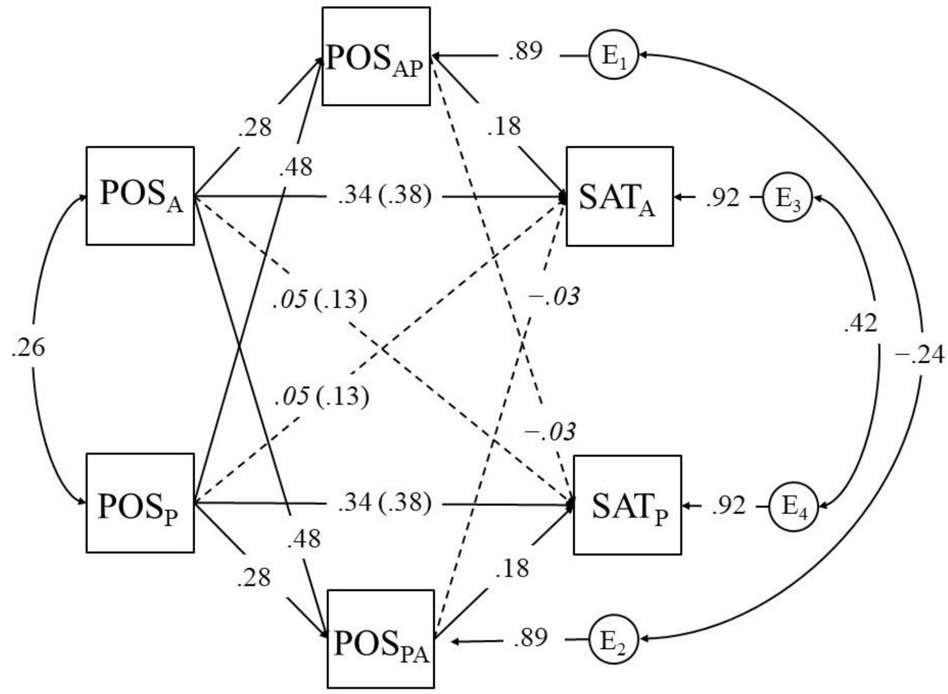

FIGURE 4
Graphical representation of results of the APIMeM, obtained controlling for the length of the relationship.

Note. Please note that estimates were obtained separately for each of the three models and are reported together in the figure. Significant paths are represented by solid lines, whereas nonsignificant paths are represented by dashed lines and italics. Total actor and partner effects are reported in brackets. POS_A = actor's positivity; POS_P = partner's positivity; SAT_A = actor's relationship satisfaction; SAT_P = partner's relationship satisfaction; POS_{AP} = actor's perception of partner's positivity; POS_{PA} =partner's perception of actor's positivity.

Step 7. Test for the Directional Bias

In Model 2, we tested the assumed similarity (or bias) effect, namely how much the actor's characteristic predicts the perception of the partner's characteristic. As we mentioned earlier, according to the literature, this effect suggests that, in perceiving their partners' characteristic, actors tend to attribute their own characteristics; in other words, they tend, in a sense, to project themselves in the partner (Kenny & Acitelli, 2001). What this effect does not tell us is if they also tend to see the partner's personality as more positive or more negative than it really is. To test if partners tended to see the other as more positively or negatively than he\she is (or, at least, how the partner describe himself/herself), we should perform the test for the directional bias. The directional bias is the extent to which a judgment tends to be biased towards one end of the judgement scale (West & Kenny, 2011).

Following the recommendations by West and Kenny (2011), the directional bias can be tested computing a model including the actor's characteristic (i.e., the bias variable) and the partner's characteristic (i.e., the truth variable) as predictors of actor's perception of the partner's characteristic (i.e., the judgement). All the variables, namely the two predictors and the outcome variable, are centered on the mean of the true value of the variable. In doing so, we can interpret the resulting intercept as the difference between the truth and the judgement mean (see West & Kenny, 2011, p. 364).

In our case, the directional bias is the extent to which the actor sees the partner as more or less positive than he\she really is. To test for the directional bias, we compute a model in which we include actor's positivity (i.e., the bias variable) and partner's positivity (i.e., the truth variable) as predictors and perceptions of actor's positivity (i.e., the judgement) as the outcome. All the variables, namely the two predictors and the outcome variable, are centered on the mean of partner's positivity (i.e., on the mean of the true value of the variable). Results of this model revealed a significant and negative effect of the intercept — $B = -.07$, $SE = .03$, $p < .05$, 95% CI [−.13, −.01] — showing that actors had a negative bias in assessing the other partner. Since we were expecting a positive bias, this last result disconfirms H5.

CONCLUSION

In this contribution, we discussed the usage of an extension of the APIM, namely the APIMeM indistinguishable using MLM. In doing so, we acknowledged the theoretical addition represented by including a mediator in the analysis. In some cases, including a mediator means giving empirical support to otherwise theoretical assumptions. For instance, the interpersonal perception framework drawn attention to whether the rater or the object of rating is responsible for a measure (Kruglanski, 1989). In particular, we presented the role of a personality trait as positivity of both partners in relationship satisfaction, predicting direct effects and indirect effects. Importantly, following the interpersonal perception theory, we included as a mediator the perception of the other partner's positivity.

Moving to discuss our findings, our first hypothesis was to find a positive effect of actor's positivity on actor's relationship satisfaction. In this regard, results confirmed our prediction, indicating that being positive results in greater relationship satisfaction. Our second hypothesis was that also partner's levels of positivity would positively predict actor's relationship satisfaction. Findings confirmed this prediction attesting that the higher the partner's positivity the greater the actor's relationship satisfaction. Our findings are not surprising and in line with the broad literature that individuated the key role of positive personality traits of both partners in predicting relationship satisfaction (Weidmann et al., 2016).

Regarding the mediation assumptions, the third hypothesis posed that actor's positivity positively predicted his/her relationship satisfaction through enhanced actor's perceptions of partner's positivity. This actor indirect effect was significant, confirming that higher bias results in greater satisfaction. This is in line with previous studies on interpersonal perception that attested how assumed similarity has a role in assuring higher satisfaction (Fletcher, 2015). However, this effect was only a little portion of the total effect (i.e., 8%), suggesting that individual positivity exerts an important role in relationship satisfaction beyond the assumed similarity effect. This partial effect opens to other possible mediators that can intervene in the relationship. One above all, the role of positivity in the promotion of emotional regulation (Caprara, Alessandri, & Barbaranelli, 2010; Caprara, Eisenberg, & Alessandri, 2017). Indeed, in previous studies on other positive personality traits, positive and negative affect revealed important predictors of relationship satisfaction (Watson, Hubbard, & Wiese, 2000). Thus, it is reasonable to expect that emotional regulation, for instance in terms of self-efficacy in managing emotions, could represent an additional mediator of this relationship.

Our fourth hypothesis was that partner's positivity exerts a positive effect on actor's relationship satisfaction, through higher actor's perception of partner's positivity. This partner indirect effect was significant and confirmed how higher accuracy leads to greater relationship satisfaction. This finding is in line with the research of interpersonal perception, which argued and demonstrated how the effect of the real characteristic passes through the image that the perceiver forms of the target. This is particularly true for romantic couples, where the other partner is directly involved in the definition of the self and identity (Kenny & Acitelli, 2001). Importantly, and on further support of this argumentation, the indirect effect was 50% of the total effect and actor's perception of partner's positivity fully mediated the relationship (i.e., the direct effect of partner's positivity was no longer significant). This latter result suggests that a large part of the partner's real level of positivity passes through the actor's lens to exert an effect on relationship satisfaction.

Lastly, results attested how bias and accuracy do not predict the other partner's relationship satisfaction. These latter findings are interesting and raise the question of whether or not the other partner is aware of the bias and accuracy effects of the actor. Reasonably, both accurate and biased perceptions of the other member of the couple's positivity do not result in visible behaviors that can inform the partner about the way the actor sees him/her. Moreover, positivity is an individual and stable disposition variable related to personal life and past, not easily changeable, and presumably individuals are less receptive to outside stimulus as the other partner's perceptions. This low receptivity, in turn, may not be sufficient to relate with relationship satisfaction. However, further studies are needed in order to address this question.

All in all, previous studies regarding Big Five personality traits already highlighted how interpersonal perceptions of agreeableness and extraversion were positive predictors of relationship satisfaction (Schaffhuser, Allemand, & Martin, 2014). On the whole, study results expand this effect to an additional positive trait as positivity. Moreover, assumed similarity and bias effects of positivity were investigated for the first time. Importantly, all the effects were found controlling for the length of the relationship. In line with the literature that shows how newly formed couples are more involved in the relationship, having a long relationship was associated to lower satisfaction (Ahmetoglu, Swami, & Chamorro-Premuzic, 2010).

Our fifth and last hypothesis posed that individuals tend to have a positive bias in assessing their partner. Accordingly, we were expecting the actor to evaluate his/her partner as more positive than the partner evaluated himself/herself (i.e., truth benchmark). This prediction was not corroborated by our data. Ultimately, our findings suggest that, for what concerns the positivity trait, individuals tend to see their partners as less positive than they really are. In other words, when considering partners' positivity, the individual is not seeing him/her through rose-tinted glasses, rather they tend to have a distort and worse image of the partner. Or, at least, worse than the image the partner has of himself/herself.

This result may be confronted with the findings obtained in the study by Caprara and colleagues (Caprara, Alessandri, Colaiaco, & Zuffianò, 2013). In their work, authors found that higher positivity predicts a higher self-enhanced phenomenon called better-than-average-effect (Alicke & Govorun, 2005) in classrooms, but not their real academic performance. We can speculate that this self-serving bias may apply also in our case and, in particular, it could intervene in assessing oneself in the case of partner's positivity. If this would be the case, it raises the question of whether the truth variable is really "true." Moreover, the self-serving bias may also intervene in the evaluation the actor makes of the other partner. However, these hypotheses need to be tested in further studies.

Ultimately, the role of the APIMeM in investigating our relationships of interest was central. Nevertheless, we should acknowledge different limits of our study, the majority of which are related to the usage of the APIMeM. First, our theoretical assumptions are based on a well-known theory; nevertheless, the design we used is cross-sectional and it limits our possibility to test causal relationships. To overcome this limit, we can think to test our assumption using experimental designs. As for any other mediation model, it is important to note that the manipulation of variables is important to exclude cofounders. With this kind of designs, couples could be assigned to different conditions, and conditions would become between-dyads variables.

Moreover, our design gives back a static image of the relationship observed, and longitudinal design could be needed in the future to study how relationships may change as a function of time. For instance, it could be interesting to study how the model may change at different levels of relationship stage or length. In this regard, the data analytic strategy would not be simple, as mediation should then be tested longitudinally, for instance using a growth curve modeling (Kashy, Donnellan, Burt, & McGue, 2008; Ledermann & Kenny, 2017). This methodology would also overcome another limitation of our study related to the specificity of our sample. Indeed, the convenience sampling we adopted resulted in a large range of participants' age and length of the relationship. Along with longitudinal studies, studies that could focus on specific ranges of age and relationship length could also lead to a better understanding of the role of life and relationship's stages in the relationships observed. In such a design, researchers could also investigate the specific effect of relationship length in relation to gender, exploring whether there are any distinguishable moderation effects of relationship length for the two members of the dyad.

Another limit of our study is related, more in general, to a typical criticism of APIMs that is the problem of the shared method variance (Orth, 2013). This criticism arises from the fact that usually, the actor's effects observed are larger than the partner's effects. Also in the interpersonal perception literature, it has been reported how assumed similarity effects are typically greater in size than accuracy effects (Fletcher & Kerr, 2010). In our study, we can observe the same tendency regarding the total actor and partner's effects, and for assumed similarity and accuracy effects. In this regard, it was pointed out how this difference in the dimension of the effects is attributable to the source of information. Especially in the case of personality traits and relationship satisfaction, scholars observed how the actor's effect is based often on information on the same source; whereas, the partner's effect is usually obtained from two variables collected from two different sources. Of course, this issue is related to self-report measures and can be overcome using different nature of indicators of relationship satisfaction, for instance, physical indicators, or third informants. Thus, we recommend that future studies can consider this issue.

Despite these limitations, the interest of scholars in different fields on the APIMeM is rapidly increasing. We can predict by now that, in the future, these models will be used more, as indicated also from recent developments and flourishing data app designed to make these models more accessible. Applications that can restructure and prepare dyadic databases for analysis and that can compute power analysis considering actor and partner effects are already available. Importantly, regarding APIMeM, to the first application developed in 2015 that uses SEM with indistinguishable dyads (Kenny, 2015) others are going to be added to simplify the usage of this complicated model. Indeed, following the same line, a recent tool was developed for SPSS, SAS, and R that can extend the analysis to distinguishable dyads (Coutts, Hayes, & Jiang, 2019). It is reasonable to expect that in the future additional tools will be available to simplify even more the usage of APIMeM.

In conclusion, in this contribution our first focus was on providing an illustrative example of the usage of an APIMeM with MLM. As we discussed earlier, MLM is particularly suited in the case of indistinguishable dyads. However, we should acknowledge that SEM is considered as the preferred method in the case of APIMeM distinguishable, especially for its ability to estimate all models' parameters in one run. Moreover, please note that the order of the steps in our tutorial is illustrative and may also be switched. For instance, researchers may decide to test distinguishability before moderation and consequently proceeding with Step 4 (test of distinguishability) before Step 3 (excluding moderation).

Our second focus was on the added value of APIMeM to different theories. In particular, we proposed positivity of both partners to account for relationship satisfaction. Although reasonable, the role of positivity had never been investigated before in previous studies. Importantly, we also had the possibility to test how interpersonal perception of positivity can intervene in this relationship. In this way, we aimed at viewing individual differences in the more complex social relationship context, by means of the accuracy-bias models. Results attested a central role of positivity and, in particular, of perceptions of positivity, in predicting relationship satisfaction. These findings support the assumptions of the interpersonal perception theory, demonstrating ultimately the added value of using an APIMeM.

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APPENDIX

#R CODE

```
#set working directory
setwd("C:/ ")

#loading the useful packages
library(dyadr)
library(foreign)

#opening the spss database
mydata <- read.spss("mydatabase.sav")
mydataf <- as.data.frame(mydata)

#variables in the database are: Dyad_ID, partnum, gender_A, age_A, relstatus, POS_A, POS_P,
POS_other_A, POS_other_P, SAT_A, SAT_P, lengthmonths
```

Step 2. Computing the Pearson's Intraclass Correlation Coefficient (ICC)

```
library(nlme)
cor.test(mydata$POS_A,mydata$POS_P)
cor.test(mydata$POS_other_A,mydata$POS_other_P)
cor.test(mydata$SAT_A,mydata$SAT_P)
```

Step 3. Excluding Moderation

```
#estimating a model with distinguishable moderation effects
#we will first need the variable gender to be a factor

mydataf$fgender_A <- factor(mydataf$gender_A)
str(mydataf)

#estimating the model

modelmod_dist <- gls(SAT_A ~ POS_A + POS_P + POS_other_A + POS_other_P + lengthmonths + gen-
der_A
        + gender_A*POS_A
        + gender_A*POS_P
        + gender_A*POS_other_A
        + gender_A*POS_other_P
        + POS_A*POS_other_A*gender_A + POS_P*POS_other_P*gender_A
        + POS_A*POS_other_P*gender_A + POS_P*POS_other_A*gender_A
        + POS_A*POS_other_A*gender_A + POS_P*POS_other_P*gender_A
        + POS_A*POS_other_P*gender_A + POS_P*POS_other_A*gender_A,
        data = mydataf,
```

```
              method = "ML",
              correlation = corCompSymm (form=~1|Dyad_ID),
              weights = varIdent(form=~1|fgender_A))

summary(modelmod_dist)

#estimating a distinguishable model where there are no moderation effects

model_dist <- gls(SAT_A ~ POS_A + POS_P + POS_other_A + POS_other_P + lengthmonths + gen-
der_A
              + gender_A*POS_A
              + gender_A*POS_P
              + gender_A*POS_other_A
              + gender_A*POS_other_P,
              data = mydataf,
              method = "ML",
              correlation = corCompSymm (form=~1|Dyad_ID),
              weights = varIdent(form=~1|fgender_A))

summary(model_dist)

#more vs less conservative model

anova(modelmod_dist, model_dist)

#estimating a model with moderation indistinghuishable

modelmod_ind  <- gls(SAT_A ~ POS_A + POS_P + POS_other_A + POS_other_P + lengthmonths +
              + POS_A*POS_other_A + POS_P*POS_other_P
              + POS_A*POS_other_P + POS_P*POS_other_A
              + POS_A*POS_other_A + POS_P*POS_other_P
              + POS_A*POS_other_P + POS_P*POS_other_A,
              data = mydataf,
              method = "ML",
              correlation = corCompSymm (form=~1|Dyad_ID))

summary(modelmod_ind)

#estimating a model indistinguishable where there are no moderation effects

model_ind <- gls(SAT_A ~ POS_A + POS_P + POS_other_A + POS_other_P + lengthmonths,
          data = mydataf,
          method = "ML",
          correlation = corCompSymm (form=~1|Dyad_ID))
```

```
summary(model_ind)
confint(model_ind, level =.95)

anova(modelmod_ind,model_ind)
```

Step 4. Test for Distinguishability

```
##Test for distinguishability: Model 1
#we will first need the variable gender as string (see above).
#we can proceed computing the model1 distinguishable.

model1_DIST <- gls(SAT_A ~ POS_A + POS_P + lengthmonths + gender_A
                + gender_A*POS_A
                + gender_A*POS_P,
                data = mydataf,
                method = "ML",
                correlation = corCompSymm(form=~1|Dyad_ID),
                weights = varIdent(form=~1|fgender_A))

summary(model1_DIST)

#estimating a model were dyads are treated as indistinguishable.

model1_IND <- gls(SAT_A ~ POS_A + POS_P + lengthmonths,
               data = mydataf,
               method = "ML",
               correlation = corCompSymm (form=~1|Dyad_ID))

summary(model1_IND)

#Test for distinguishability: comparing the two models parameters using the function "anova".
anova(model1_DIST, model1_IND)

##Test for distinguishability: Model 2

model2_DIST <- gls(POS_other_A ~ POS_A + POS_P + lengthmonths + gender_A
              + gender_A*POS_A
              + gender_A*POS_P,
              data = mydataf,
              method = "ML",
              correlation = corCompSymm(form=~1|Dyad_ID),
              weights = varIdent(form=~1|fgender_A))
```

```
summary(model2_DIST)

model2_IND <- gls(POS_other_A ~ POS_A + POS_P + lengthmonths,
            data = mydataf,
            method = "ML",
            correlation = corCompSymm (form=~1|Dyad_ID))

summary(model2_IND)

#test
anova(model2_DIST, model2_IND)

##Test for distinguishability: Model 3

#distinguishable model

model3_DIST <- gls(SAT_A ~ POS_A + POS_P + POS_other_A + POS_other_P + lengthmonths + gen-
der_A
             + gender_A*POS_other_A
             + gender_A*POS_other_P
             + gender_A*POS_A
             + gender_A*POS_P,
             data = mydataf,
             method = "ML",
             correlation = corCompSymm(form=~1|Dyad_ID),
             weights = varIdent(form=~1|fgender_A))

summary(model3_DIST)

#indistinghuishable model

model3_IND <- gls(SAT_A ~ POS_A + POS_P + POS_other_A + POS_other_P + lengthmonths,
            data = mydataf,
            method = "ML",
            correlation = corCompSymm (form=~1|Dyad_ID))

summary(model3_IND)

#test
anova(model3_DIST, model3_IND)
```

Step 5. Estimating the APIMeM indistinguishable.
##a. Standardization of variables

```
#Computing means and standard deviations for all variables
```

```
meanlengthmonths = mean(mydataf$lengthmonths)
sdlengthmonths = sd(mydataf$lengthmonths)

meanPOS_A = mean(mydataf$POS_A)
sdPOS_A = sd(mydataf$POS_A)

meanPOS_P = mean(mydataf$POS_P)
sdPOS_P = sd(mydataf$POS_P)

meanPOS_other_A = mean(mydataf$POS_other_A,)
sdPOS_other_A = sd(mydataf$POS_other_A)

meanPOS_other_P = mean(mydataf$POS_other_P)
sdPOS_other_P = sd(mydataf$POS_other_P)

meanSAT_A = mean(mydataf$SAT_A)
sdSAT_A = sd(mydataf$SAT_A)

meanSAT_P = mean(mydataf$SAT_P)
sdSAT_P = sd(mydataf$SAT_P)

#Creating a new variable named e.g. "namevariable_s" that is equal (namevariable - meannamevaria-
ble)/sdnamevariable.

mydataf$POS_As = (mydataf$POS_A - meanPOS_A)/sdPOS_A
mydataf$POS_Ps = (mydataf$POS_P - meanPOS_P)/sdPOS_P
mydataf$POS_other_As = (mydataf$POS_other_A - meanPOS_other_A)/sdPOS_other_A
mydataf$POS_other_Ps = (mydataf$POS_other_P - meanPOS_other_P)/sdPOS_other_P
mydataf$lengthmonths_s = (mydataf$lengthmonths- meanlengthmonths)/sdlengthmonths
mydataf$SAT_As = (mydataf$SAT_A - meanSAT_A)/sdSAT_A
mydataf$SAT_Ps = (mydataf$SAT_P - meanSAT_P)/sdSAT_P

summary(mydataf) #check if the variables were included in the dataframe
```

##b. The four steps.

```
#Step 1: Detecting total effects of the two proposed predictors, controlling for the covariate(s).
model1 <- gls(SAT_As ~ POS_As + POS_Ps + lengthmonths_s,
        data = mydataf,
        method = "ML",
        correlation = corCompSymm (form=~1|Dyad_ID))

summary(model1)
confint(model1, level =.95)
```

```
#Step 2: Detecting effects of the predictors on the mediator, controlling for the covariate(s).
model2 <- gls(POS_other_As ~ POS_As + POS_Ps + lengthmonths_s,
        data = mydataf,
        method = "ML",
        correlation = corCompSymm (form=~1|Dyad_ID))

summary(model2)
confint(model2, level =.95)

#the path in the figure from variables to errors
sqrt(0.7845001)

#Step 3 and Step 4: Detecting the effect of the mediator on the outcome, controlling for the other predictors and the covariate(s). At the same time, obtaining direct effects of the predictors.

model3 <- gls(SAT_As ~ POS_other_As + POS_other_Ps + POS_As + POS_Ps + lengthmonths_s,
        data = mydataf,
        method = "ML",
        correlation = corCompSymm (form=~1|Dyad_ID))

summary(model3)
confint(model3, level =.95)

#the path in the figure from variables to errors
sqrt(0.8454181)
```

##c. Obtaining the R squared.

```
#Comparing sd of errors of Model1 with an empty model.
#1. Computing the empty model1.
model_empty1 <- gls(SAT_As ~ 1,
          correlation=corCompSymm (form=~1|Dyad_ID),
          data=mydataf)
summary(model_empty1)

model_empty2 <- gls(POS_other_As ~ 1,
          correlation=corCompSymm (form=~1|Dyad_ID),
          data=mydataf)
summary(model_empty2)


# sd of errors for model1
m1 = as.numeric(model1$sigma)
# sd of errors for model2
m2 = as.numeric(model2$sigma)
```

```
# sd of errors for model3
m3 = as.numeric(model3$sigma)
# sd of errors for the empty model1
mE1 = as.numeric(model_empty1$sigma)
# sd of errors for the empty model2
mE2 = as.numeric(model_empty2$sigma)

# the R squared, using the "crsp" function
crsp (m1,mE1)
crsp (m2,mE2)
crsp (m3,mE1)
```

##d. Getting the partial ICC

```
coef(model1$model$corStruct, unconstrained = FALSE)
coef(model2$model$corStruct, unconstrained = FALSE)
coef(model3$model$corStruct, unconstrained = FALSE)
```

##e. Indirect effects.

```
#1. We obtain the single effects from the model computed above.
#a X-> M effects and standard errors
act_a <- coef(summary(model2)) [2,1]
part_a <- coef(summary(model2))[3,1]
act_a_se <- coef(summary(model2)) [2,2]
part_a_se <- coef(summary(model2)) [3,2]
# M -> Y effects
act_b <- coef(summary(model3))[2,1]
part_b <- coef(summary(model3))[3,1]
act_b_se <- coef(summary(model3))[2,2]
part_b_se <- coef(summary(model3))[3,2]
# c or X --> Y total effects
act_c <- coef(summary(model1))[2,1]
part_c <- coef(summary(model1))[3,1]
# cp or X --> Y direct effects
act_cp <- coef(summary(model3))[4,1]
part_cp <- coef(summary(model3))[5,1]

#2. We compute the indirect effects.
# Actor-Actor (actor IE: XA on YA through MA and XP on YP through MP)
AA_IE <- act_a*act_b
# Actor-Partner (actor IE: XA on YA through MP and XP on YP through MA)
AP_IE <- act_a*part_b
# Partner-Actor (partner IE: XA on YP through MA and XP on YA through MP)
PA_IE <- part_a*act_b
# Partner-Partner (partner IE: XA on YP through MP and XP on YA through MA)
```

```
PP_IE <- part_a*part_b

#3. We ask the 95% confidence intervals for each indirect effect (default on 10,000 runs).
# for AA indrect effect:
CI_AA = mmc(act_a, act_b, act_a_se, act_b_se)
# for AP indrect effect:
CI_AP = mmc(act_a, part_b, act_a_se, part_b_se)
# for PA indrect effect:
CI_PA = mmc(part_a, act_b, part_a_se, act_b_se)
# for Men PP indrect effect:
CI_PP = mmc(part_a, part_b, part_a_se, part_b_se)

#4. We ask to see the indirect effects and the related confidence intervals computed above.
AA_IE
AP_IE
PA_IE
PP_IE

CI_AA
CI_AP
CI_PA
CI_PP
```

###Step 7. Test for the Directional Bias.

```
#We grand mean center the truth variable (POS_P), the bias variable (POS_A) and the judgment variable (POS_other_A) on the truth mean.

meanPOS_P = mean(mydataf$POS_P)

mydataf$TCPOS_A = mydataf$POS_A - meanPOS_P
mydataf$TCPOS_P = mydataf$POS_P - meanPOS_P
mydataf$TCPOS_other_A = mydataf$POS_other_A - meanPOS_P

summary(mydataf) #check

model_dbias <- gls(TCPOS_other_A ~ TCPOS_A + TCPOS_P,
              data = mydataf,
              method = "ML",
              correlation = corCompSymm (form=~1|Dyad_ID))

summary(model_dbias)
confint(model_dbias, level =.95)
```