MethodsX 13 (2024) 103022

Contents lists available at ScienceDirect

MethodsX

journal homepage: www.elsevier.com/locate/methodsx

A method for the analysis of data about dyadic relationships ☆,☆☆

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ARTICLE INFO

Method name:
Application of the bifactor model to dyadic data

Keywords:
Dyadic data
Relationship data
Bifactor model
Husband-wife data

ABSTRACT

Psychological research in many subfields focuses on dyads and dyadic relationships because they influence individual cognitions, emotions, and behavior. However, the measurement of relationship characteristics has been elusive. Although direct observational methods have been hailed as the gold standard, they have some disadvantages, such as their high cost and external validity. We propose a factor-analytic method, specifically the bifactor model, using self-report data from each individual of a dyad. This method has been applied to many contexts but not yet to dyadic data. We show that the information that can be gleaned from these data is relatively low-cost but rich in terms of the insight it yields about the nature of the dyadic relationship. We demonstrate two different applications of the bifactor model to data from married couples.

- The bifactor model can be used to identify the individual-specific and dyadic aspects of data reported by the members of a dyad.
- The estimates of the bifactor model of dyadic data can yield information about hierarchical aspects of a relationship, which are not directly assessed.

Specifications table

Subject area:	Psychology
More specific subject area:	Psychological measurement, family psychology; social psychology; psychological methods
Name of your method:	Application of the bifactor model to dyadic data
Name and reference of original method:	Bifactor model Reise, S. P. (2012). The Rediscovery of Bifactor Measurement Models. Multivariate Behavioral Research, 47(5), 667–696. https://doi.org/10.1080/00273171.2012.715555
Resource availability:	Sample MPLUS input statements and demonstration data are provided in Supplementary Materials.

Background

Psychological research in many subfields requires relationships to be the focus rather than individuals. A dyadic relationship is the simplest form. A dyad (e.g., a couple, friends, a parent and a child) transforms from two individuals interacting to an entity of its own because of sustained interactions. That entity is distinct from, but influenced by, and exerts lasting influences on each individual. Yet, the measurement of dyadic characteristics remains elusive. We propose a low-cost factor-analytic method using self-report data that has been applied to many other contexts but not yet to dyadic data.

☆ **Related research article:** None.
☆☆ **For a published article:** None.
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https://doi.org/10.1016/j.mex.2024.103022
Received 17 October 2024; Accepted 24 October 2024
Available online 8 November 2024
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This research was motivated by a need to measure dyadic emotions and cognitions that may predict the behaviors of married couples during conflict, but the method shown here can be applied to any data reported by multiple informants about the characteristics of their relationship. The proposed method was validated using self-report data from spouses' positive problem-solving skills and perceived marital dysfunction.

Most of our knowledge on the effects of individual characteristics on relationship-related outcomes comes from research using Actor-Partner Interdependence Models (APIM) and observational methods of assessing dyadic characteristics. The studies using APIM found that the characteristics of the respondent and those of the partner linearly and interactively predicted their own and their partner's outcomes [6]. However, the APIM models do not attempt to identify the characteristics of the dyadic relationship but rather the mutual effects of the members of a dyad. As such, APIM estimates confound the effects of the actor and the partner with the dyadic effects [14].

Studies using real-time observational data on dyadic interactions employ coding frames developed for this purpose [7]. This direct approach to assessing dyadic characteristics requires lab-based studies where the members of a dyad are asked to simulate an interaction (e.g., through a problem-solving task) to be coded. Observational data allows insight into the real-time interactions [5]. However, they are costly, based on interactions that occur in a short time interval in a non-natural setting, and they are limited by the coders' perception of the situation [2].

In the current study, we employ a factor analytic method that allows the identification of three sources of variance in dyadic characteristics: the variance that can be attributed to each individual's characteristics and the variance that can be attributed to the dyadic characteristics. Our approach and the alternative direct observational approaches have different strengths and weaknesses. Our proposed method uses low-cost self-report data from the members of a dyadic relationship about *their* perceptions of their *naturally occurring* interactions. At the same time, self-report information on dyadic characteristics is limited by the informants' perceptions of and attributions about the other and their self-awareness in dyadic interactions.

Method overview

Fig. 1 displays the general structure of the proposed measurement model to test whether a characteristic is an individual characteristic, a dyadic characteristic, or both. This is an application of a standard bifactor confirmatory factor analysis (CFA) model (see, [10]). If a certain characteristic does not have a dyadic component (shown in Fig. 2), then the latent variable representing the shared variance of all items reported by both individuals will have a non-significant variance, and the model shown in Fig. 1 will have goodness of fit indicators that are not significantly different from a model that omits the dyadic latent variable (see, for example, [3]). In that case, the model displayed in Fig. 1 will be rejected in favor of the one displayed in Fig. 2 because the former has too many redundant parameters (smaller degrees of freedom).

Similarly, if a certain characteristic is a dyadic characteristic without idiosyncratic individual components (shown in Fig. 3), then the latent variables representing individual-specific characteristics will have non-significant variances, and the model shown in Fig. 1 will be rejected in favor of the one displayed in Fig. 3, as before. If a characteristic has both individual and dyadic components, then the estimated variances of all three latent variables shown in Fig. 1 will be statistically significant, and the bifactor model will have a significantly better comparative fit than individual-only or dyad-only models despite its lower degrees of freedom.

In some applications of the bifactor model, it was noted that cross-loading of the items on more than a single latent sub-factor (i.e., a complex factor structure) may be a cause for concern [10]. When the bifactor model is applied to dyadic data, this is not a concern because the informant of each item is evident, and the individual-specific latent factors are specified accordingly.

Evaluation of the model fit

The overall goodness of fit of the bifactor model can be assessed by the commonly reported statistics such as the likelihood ratio chi-square (χ^2), root mean square error of approximation (*RMSEA*), comparative fit index (*CFI*), and squared mean square residual (*SMSR*). When comparing alternative bifactor models, one must choose what comparative fit indices and what criteria will be used. If nested models are compared, then a conservative test would be the nested χ^2 test. Bayesian comparative statistics can also be used such as the Akaike information criterion (*AIC*) and Bayesian information criterion (*BIC*), although the latter two do not have broadly agreed upon criteria. A discussion of the use of overall and comparative goodness of fit statistics and their differences is beyond the scope of the current study (see [13]).

Additional conceptually meaningful model statistics

In addition to representing data on relationships in terms of its individual and dyadic components, the proposed bifactor model yields two types of estimates: (i) estimates that provide information about the hierarchical nature of the dyadic relationship, and (ii) estimates of the psychometric qualities of the individual-specific and dyadic latent factors. The factor loadings for each latent factor can be valuable to highlight those items that are most likely to characterize the corresponding latent factor. For example, if the items that were reported by one individual have consistently, substantially, and significantly higher loadings on the dyadic latent factor, it can be an indication of the disproportionate influence of that individual on the dyadic relationship.

Selected psychometric statistics that can be obtained from the estimated factor loadings and their interpretations are listed in Table 1. These statistics were selected because their interpretations would be helpful for the specific application of bifactor models for relationship data. These indicators are readily available using an Excel spreadsheet made available by Dueber [4].



Fig. 1. The general structure of the proposed bifactor model for dyadic data. *Note*: Rectangles represent observed indicators, and ovals represent latent variables.

Table 1
Selected psychometric statistics for the individual and dyadic latent factors.

Psychometric Indicator	Interpretation of the psychometric statistic in the case of bifactor models for dyadic relationship data
Explained common variance for the dyadic latent variables, *ECV-D*	*ECV-D* is the degree to which the dyadic latent variable accounts for the variance in all of its observed indicators reported by both members of the dyad.
Explained common variance for individual specific latent variables, *ECV-I*	*ECV-I* is the degree to which that individual-specific latent variable accounts for the variance in its observed indicators relative to the total variance accounted for in those indicators by both the dyadic latent variable and the individual-specific latent variable.
Item level explained common variance, *IECV*	This is a statistic that is available for every item that contributes to both the dyadic and the individual-specific latent variables and it provides the proportion of variance in each item that can be attributed to the variance in the dyadic latent variable.
Relative omega of the dyadic latent variable, ω_R	ω_R is a measure of the proportion of reliable variance in the composite of all indicators that can be attributed to the dyadic latent variable
Relative omega of the individual-specific latent variables ω_R-I	ω_R-I is a measure of the proportion of reliable variance in the composite of all indicators of that individual-specific latent variable that can be attributed uniquely to the corresponding individual-specific latent variable but not the dyadic latent variable.
Determinacy of the dyadic factor, *FD-D*	*FD-D* represents the degree to which the estimated value of the dyadic latent variable is closely correlated with the value of the theoretical underlying dyadic latent variable. Alternatively, it can be interpreted as an estimate of how consistently we will be able to rank-order the dyads based on the theoretically possible numerous estimated values of their dyadic latent variable.
Determinacy of the individual factors, *FD-I*	*FD-I* represents the degree to which the estimated value of the individual-specific latent variable is closely correlated with the value of the theoretical underlying individual latent variable. It can also be interpreted as an estimate of the degree of consistency by which we can rank-order the individuals based on the theoretically possible numerous estimated values of their individual-specific latent variable.

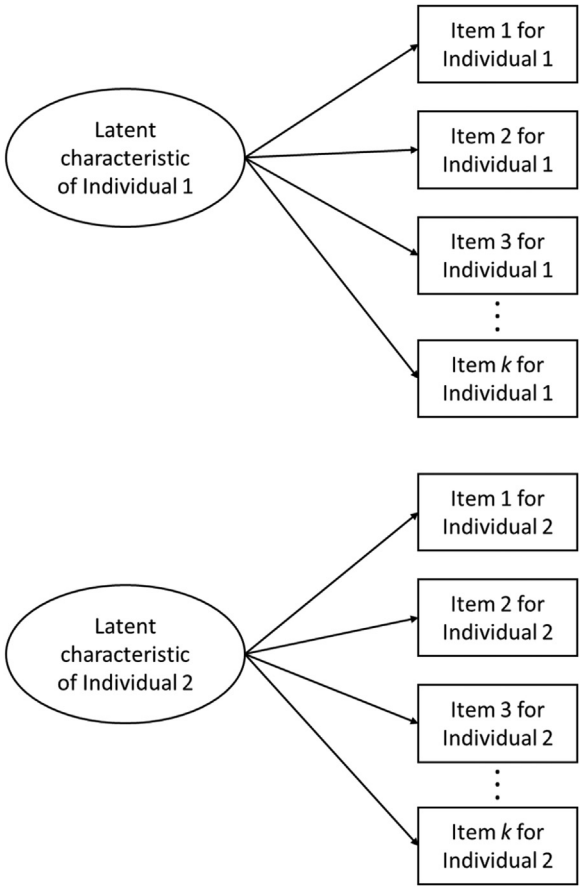


Fig. 2. The general structure of the bifactor model if a dyadic component is not supported by the data. *Note*: Rectangles represent observed indicators, and ovals represent latent variables.

The specification of the parameter constraints for the dyadic bifactor model

When dyadic data are concerned, conceptual considerations must influence the way model constraints will be specified to ensure statistical identification and meaningful interpretation. These considerations involve when to equate intercepts, variances, or factor loadings. Some guidelines are discussed here. However, the nature of the latent characteristic that is being modeled, the nature of the relationship for which we have data, and the expectations about each individual's perception of that relationship characteristic must play a role in the specification of the constraints.

Case 1: A dyad of individuals with a status differential

We start our discussion from an example where dyadic data come from two individuals with a status differential but not a difference in underlying skills. An example would be when we analyze the effectiveness of communication between an employee and a supervisor. Each individual may have equal underlying communication skills, but we may not have the expectation that an item reported by the supervisor and the employee will equally contribute to the effectiveness of the dyadic communication. The constraints shown in Fig. 4 represent a model that may be appropriate for this case.

First, for model identification, all latent characteristics must be specified as independent, i.e., their covariances must be set to zero. Next, constraints that represent metric and scalar measurement invariance in the individual-specific latent characteristics must be specified because each member of the dyad is expected to have reported on the same latent characteristic of the dyad. Hence, the factor loadings (shown by λ) and the intercepts (shown by α) of the indicators are constrained to be equal. However, we have no expectation that the two individuals will have equal levels of the latent characteristic. To ensure identification, the intercept of one of the individual-specific latent characteristic is constrained to zero, and one is freely estimated.

The dyadic latent characteristic, on the other hand, may favor some indicators of one individual over the other. For example, for dyadic communication to be effective, the supervisor's clear communication of expectations may be more important than that of the employee. The estimated factor loadings of the dyadic latent factor and their standard errors can be compared to test whether this conceptually relevant hypothesis is supported by the data.

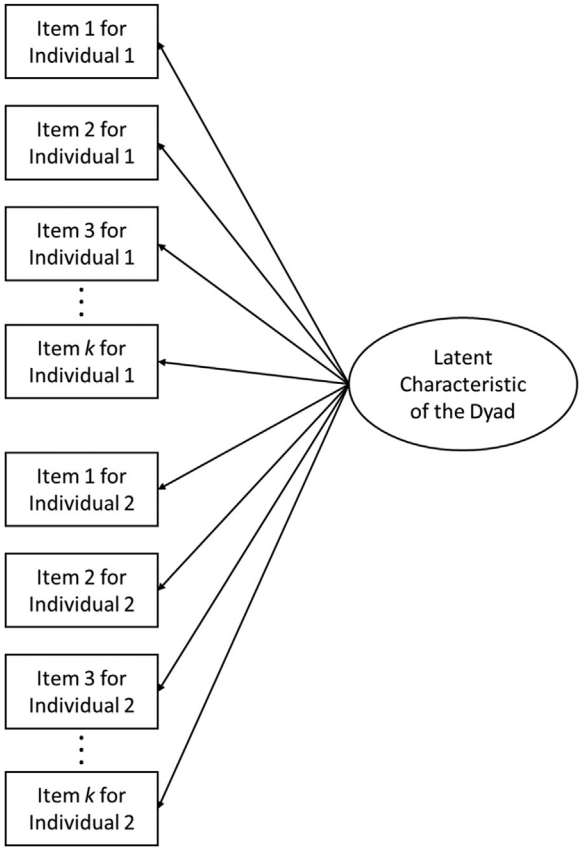


Fig. 3. The general structure of the bifactor model if individual-specific components are not supported by the data. *Note*: Rectangles represent observed indicators and ovals represent latent variables.

Case 2: A dyad of individuals with a status differential and an expected difference in their individual-specific latent characteristics

It is possible that the dyad consists of two individuals who not only have a difference in status but also differences in the way they attribute meaning to the characteristics of their relationship. A parent-child relationship is an example of this. The parent is expected to have more control in regulating dyadic interactions. Furthermore, a parent's and a child's underlying skills of conflict management are expected to be different not only quantitatively, but qualitatively as well, because of maturational differences. Even if the parent and the child respond to identical items (e.g., whether they listen to each other), their perception of the same interaction will qualitatively differ. In this case, the two individuals will not have the same conceptual definitions of the individual-specific latent characteristic, and they are not expected to contribute equally to the latent dyadic characteristic.

To specify a model that represents Case 2, the constraints imposed on the loadings on the individual-specific latent characteristics (shown in Fig. 4 as λ_1-λ_4) must be lifted. The loadings of each of the observed indicators for each individual must be distinct. Hence, for individual 2, the λ parameters λ_1 to λ_4 must be replaced with λ_5 to λ_8, where λ_5 is constrained to be 1. In addition, the intercept of the latent characteristic for individual 2 (α_2^I) must also be constrained to be equal to 0 to ensure statistical identification. Despite the fact that both individual-specific latent factors will have intercepts of zero, this constraint will not imply equal mean levels because the two latent variables are modeled as qualitatively distinct. Each indicator is expected to have unique loadings on the dyadic latent variable, whether reported by the parent or the child. This model provides a tool to test whether any individual-specific skills contribute disproportionately, or not at all, to the dyadic latent characteristic.

The specification of the bifactor dyadic model when item responses are ordinal

The item responses to measures commonly used in psychology are ordinal with 3-point, 5-point, or 7-point Likert rating scales. If the indicators are ordinal, and especially if the ordinal responses are heaped, it is more appropriate to use model specifications that accommodate ordinal observed indicators [8]. This is done under the assumption that the ordinal data for each one of the items are generated by an underlying normally distributed variable. The observed ordinal ratings are modeled as the indicators of the cutoff points (i.e., the thresholds) on that continuous distribution. Therefore, one must consider the constraints that must be placed on the

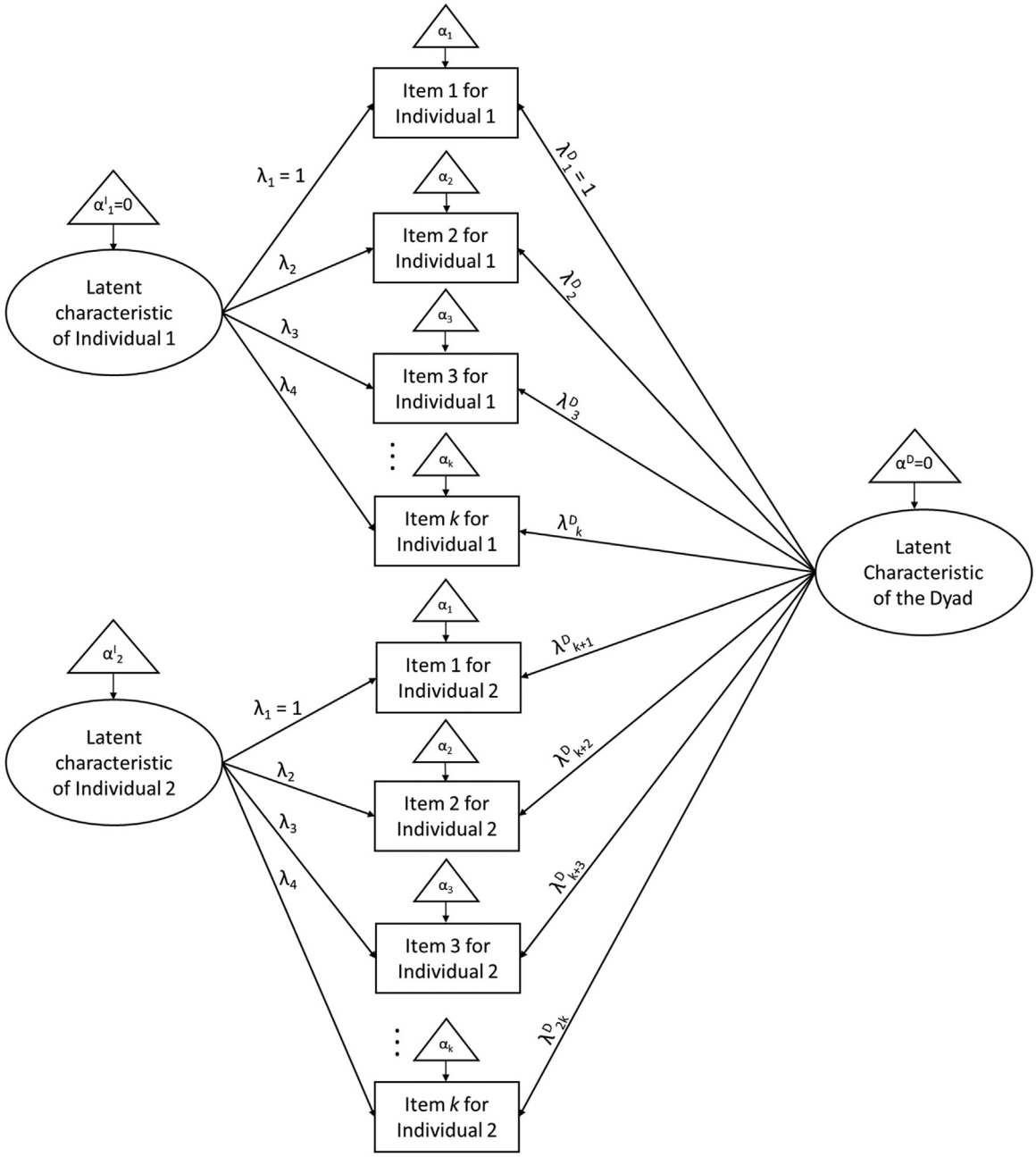


Fig. 4. The parameter constraints that can be used for Case 1. *Note*: Rectangles represent observed indicators; ovals represent latent variables; and, triangles represent intercepts. Error variances of the observed indicators are not shown. A superscript of I denotes individual specific, and a superscript of D denotes dyadic.

values of the thresholds that are estimated by the observed ordinal data. As a general principle, the thresholds can be constrained in the same way the intercepts are constrained using the same considerations that are discussed in Case 1 and Case 2 above.

Methodologically speaking, the estimation of the bifactor models with ordinal data does not present much difficulty, but some issues arise in practice. If any category of any one of the items is too sparsely populated to identify the thresholds, some categories must be collapsed, resulting in a loss of information. The number of parameters that are estimated with such models is large. Two issues arise with large numbers of parameters: the sample sizes required to estimate large numbers of parameters often exceed the typical sample sizes of psychological studies. Without large sample sizes, the estimation algorithms may become unstable. In that case, it may be advantageous to use more robust estimators, such as the weighted least squares. However, using robust estimators does not address the issue of inadequate statistical power.

Table 2
The goodness of fit statistics of the bifactor models for Case 1, positive marital problem-solving (n = 731).

Goodness of fit statistics	Model			
	Model A A dyadic latent factor and individual-specific factors for the wife and the husband	Model B Only individual-specific latent factors	Model C Only a dyadic latent factor	Model D A dyadic latent factor and an individual-specific latent factor for the wife
χ^2	13.3	58.9	153.7	13.6
df	6	12	8	7
p	0.038	<0.001	<0.001	0.059
RMSEA	0.042	0.075	0.162	0.037
CFI	0.99	0.92	0.75	0.99
χ^2 *diff*		45.6	140.4	0.3
df diff		6	2	1
p		<0.001	<0.001	0.58
AIC	3013.3	3046.8	3149.7	3011.6
AIC diff[2]		33.5	136.4	1.7
BIC	3042.1	3067.4	3236.1	3039
BIC diff[2]		25.3	194	3.1

Notes:.
1. The model that includes both individual and dyadic latent variables was the comparison model because the remaining models were nested under that one.
2. AIC and BIC comparison criteria were set as 6.0 points [9].

If the number of categories of ordinal ratings is large enough, they may be assumed to be continuous indicators without compromising the estimates [11], allowing the use of standard model estimators. However, providing a large number of rating points tends to lead to heaping of data in certain categories, or worse, responses with large random measurement errors. As a result, an alternative solution can be used. Items that are conceptually similar can be combined to yield item "packets." While a loss of information is still inherent in this approach, it may be viable when the number of items is large, but the sample size is not large enough to support analyzing the responses as ordinal data.

Method validation

We provide two examples of the application of dyadic bifactor models. The first is an application of Case 1, as discussed above. The data are on the marital problem-solving approaches of married couples [1]. The second is an application of Case 2, using data on marital dysfunction.

Application of case 1: Marital problem-solving approaches

Data and distributional assumptions: Case 1 used data on eight items on positive problem-solving that were rated by wives and husbands (n = 731 couples) on a scale of 1–5 (not at all true to completely true). These eight items were combined into three item packets for which continuous distributions were assumed.

Model building: the bifactor model was tested (Model A, Fig. 1) as well as a model of individual-specific factors (Model B, Fig. 2) and a model of a single dyadic factor (Model C, Fig. 3). Table 2 shows the goodness of fit statistics. The bifactor model had a very good fit, and the comparative fit statistics indicated that neither Model B nor C compared favorably to Model A. The psychometric statistics of the dyadic and individual-specific latent characteristics were investigated using the indicators described in Table 1.

Although the overall fit indicators of the bifactor model were satisfactory, the indicators of the psychometric quality of the estimated individual-specific and dyadic factors were poor (Table 3). First, *ECV-D* was 0.52, indicating that the dyadic positive problem-solving accounted for about half of the combined variance in all of the item packets. Therefore, the presence of individual-specific positive problem-solving skills was likely. Indeed, *ECV-I* for the wife was 0.72, quite substantial for a subfactor. However, *ECV-I* for the husband was only 0.24, suggesting that the variance in husband-reported items was mainly due to the dyadic factor.

Other psychometric statistics of the latent factors were in line with the *ECV-D* and *ECV-I*. For example, ω_R-I value was very low for the husband's latent factor (0.25), pointing to a low proportion of reliable variance in the husband's latent factor. At the item level, while the wife's *IECV* values were low (0.08 to 0.35), yielding strong evidence of the existence of an idiosyncratic latent factor for the wife, the *IECV* values for the husband-reported items were high (0.60 to 0.80).

The selection of the final model: The analyses presented above pointed to a bifactor model that included a dyadic positive problem-solving factor and a wife's specific positive problem-solving factor but no husband-specific factor (Model D). Both the goodness of fit indicators (Table 2, last column) and the statistics indicating the psychometric quality of the estimated factors (Table 3, last column) for Model D were satisfactory. The factor-level indicators of psychometric quality were sufficiently high to warrant the estimation of factor scores for the dyadic and wife-specific positive problem-solving that could be used in further analyses.

Table 3
Psychometric statistics for the latent factors estimated by Model A and Model D for Case 1, positive marital problem-solving (n = 731).

Psychometric statistics for the latent factors[1]	Model	
	Model A A dyadic latent factor and individual-specific factors for the wife and the husband	Model D A dyadic latent factor and an individual-specific latent factor for the wife
ECV-D	0.52	0.60
ECV-I (wife)	0.72	0.78
ECV-I (husband)	0.24	–
ω_R	0.65	0.72
ω_R-I (wife)	0.74	0.80
ω_R-I (husband)	0.25	–
FD-D	0.76	0.83
FD-I (wife)	0.73	0.75
FD-I (husband)	0.42	–

Note: 1. See Table 1 for the acronyms and their interpretations.

Table 4
Psychometric statistics for the latent factors estimated for Case 2, marital dysfunction (n = 693).

Psychometric statistics for the latent factors[1]	Model A A dyadic latent factor and individual-specific factors for the wife and the husband
ECV-D	0.57
ECV-I (wife)	0.40
ECV-I (husband)	0.48
ω_R	0.73
ω_R-I (wife)	0.40
ω_R-I (husband)	0.47
FD-D	0.85
FD-I (wife)	0.77
FD-I (husband)	0.78

Note: 1. See Table 1 for the acronyms and their interpretations.

The final model also yielded an example of empirical evidence for the status differential of the husband and the wife. The indicators of the husbands' problem-solving skills had factor loadings on the dyadic latent factor that exceeded those of the wives' by 55 % to over 100 %, suggesting the status differential at play in their attempts to solve marital problems.

Application of case 2: marital dysfunction

Data and distributional assumptions: Although marital dysfunction is a dyadic characteristic by definition, it is highly likely that the perceptions of the wife and the husband regarding the nature and the extent of dysfunction may differ. The data consists of eight items on the spouses' perceptions of whether their expectations of support are met, rated on a scale of 1–3. The ratings of all items were strongly heaped in the category expressing no dysfunction. These data were modeled as ordinal data because of the heaping and the limited range of the rating scale (n = 693 couples).

Model building: First, a bifactor model was tested that did not assume measurement invariance for the spouse-specific latent factors. Next, a model that assumed metric invariance and a model that assumed scalar invariance were estimated. The goodness of fit of the metric invariance model was not significantly different from that of the unconstrained model ($\chi^2(7) = 9.5$, *n.s.*), but the scalar invariance model yielded a significantly worse fit than the metric invariance model ($\chi^2(15) = 164.3$, $p < .001$). We proceeded with the model assuming that the factor loadings on the wife's and the husband's specific latent factors were equal but that the two factors did not have scalar invariance. In other words, the wives' and the husbands' thresholds to perceive dysfunction differed. Specifically, the husbands' had a higher threshold for perceiving dysfunction than their wives on seven of the eight items. Model A had satisfactory goodness of fit ($\chi^2(95) = 116.4$, $p = .07$, $RMSEA = 0.02$, $CFI = 0.99$, $SRMR = 0.07$).

Similar to the Case 1, two alternative models were tested. Model B with no dyadic marital dysfunction factor, and Model C with no individual-specific marital dysfunction factors. These models had goodness of fit indicators that were far inferior to the bifactor model ($\chi^2_{diff}(16) = 207.5$, $p < .001$ and $\chi^2_{diff}(9) = 124.5$, $p < .001$).

Table 4 lists the factor-level indicators of the psychometric statistics for the dyadic, wife's, and husband's latent marital dysfunction factors. *ECV-D* and *ECV-I* values for both of the spouse-specific latent factors indicated that each one of these latent factors accounted for substantial proportions of the combined variance in the corresponding items. *FD-D* and *FD-I* values also indicated that the factor scores of all three latent factors could rank-order the members of the sample fairly consistently. However, ω_R-I values for the spouse-specific latent factors were far from adequate. Therefore, the proportions of reliable variance in those latent factors independent of the dyadic factor were low, precluding the use of those latent factor scores in analyses that do not control for the dyadic factor [12].

The examination of the item-level statistics revealed that one of the items (the item representing the perception of insufficient physical care received from the spouse) did not have sufficient spouse-specific variance (*IECV* values of 0.86 and 0.78 for the wife and the husband, respectively).

The selection of the final model: Although the analyses presented as Case 2 pointed to a bifactor model that included a dyadic and two spouse-specific marital dysfunction factors, the latter two did not have adequate reliability independent of the dyadic factor. Based on the item-specific statistics, it is likely that the exclusion of the item with high *IECV* values from the spouse-specific factors may lead to acceptable ω_R-I values. Nevertheless, if factor scores are estimated based on Model A, their use in analyses that do not control for the dyadic marital dysfunction factor would be inadvisable.

Limitations

When dyadic bifactor models are estimated, there may be conceptual reasons why individual-specific latent factors are of interest, as well as the dyadic factor. However, the estimated individual-specific latent factors tend to have low reliabilities because much of the combined variance of the items may be accounted for by the dyadic latent factor. Three recommendations may be relevant in this case.

First, if the individual-specific latent factors are used as independent variables in a model, the entirety of the measurement model may be incorporated into the analyses so that the dyadic latent factor can be accounted for and the error terms are explicitly modeled. Second, any effects of the individual-specific latent factors on the dependent variables should be subjected to rigorous probing for robustness. Third, the items themselves may be re-examined, and the wording may be revised to emphasize an individual's unique characteristics. Nevertheless, if we find that the dyadic latent factor overwhelms the combined variance of all items, then a straightforward interpretation may be the correct one: individuals' characteristics (i.e., cognitions or behaviors) are transformed when they are in sustained dyadic relationships, and a truly dyadic characteristic emerges.

Ethics statements

The data that was used for the applications presented in this study was collected from a nationally representative sample with explicit verbal consent, as approved by the institutional review board of the author's institution (2018.157.IRB3.113).

CRediT author statement

Nazli Baydar designed and applied the method described here, wrote the first draft of this manuscript and, prepared the final draft for publication. Mehmet Eskin assisted in collecting the data used for method validation and reviewed and edited the draft.

During the preparation of this work the author(s) used Grammarly in order to improve grammar and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have shared the demonstration data as supplementary materials. The demonstartion data has no identifiers on the shared file.

Acknowledgments

This research was funded by the Scientific and Technological Research Council of Türkiye grant 119K365. The idea of using bifactor models for dyadic data was inspired by Begum Dora's work, which used bifactor models to analyze the components of marital dysfunction.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.mex.2024.103022.

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