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A confirmatory composite analysis for the Italian validation of the interactions anxiousness scale: a higher-order version

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Abstract
This study examined the factor structure and model specifications of the Interaction
Anxiousness Scale (IAS) with confirmatory composite analysis (CCA) using partial
least squares-structural equation modeling (PLS-SEM) with a sample of Italian ado-
lescents ($n = 764$). The CCA and PLS-SEM results identified the reflective nature
of the IAS sub-scale scores, supporting an alternative measurement model of the
IAS scores as a second-order reflective–reflective model.

Keywords Interactions Anxiousness Scale · Partial least squares · Confirmatory
composite analysis · Structural equation model · Higher-order · Adolescents

1 Introduction

Social anxiety is defined as "a state of anxiety resulting from the prospect or
presence of interpersonal evaluation in real or imagined social settings" (Leary
and Schlenker 1981). Although it is usually associated with specific behavioural
manifestations in social interactions, such as avoidance, hesitancy and awkward-
ness, it should be intended as a merely subjective experience, independent from
specific overt behaviours (Leary 1983): indeed, the presence of individual anxiety
is not necessarily accompanied by the other, so that people who are able to man-
age and hide their anxiety could behave competently, and, conversely, people who
show avoidant, hesitant, or awkward behaviours could not report social anxiety.
At the basis of social anxiety (or sometimes known as social anxiousness) there
is a concern with the others' perceptions and evaluations at the moment of an

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interaction or/and at the prospect of participating in a particular encounter, across different social situations and time.

Starting from this premises, Leary (1983) has developed an instrument, namely "Interactions Anxiousness Scale (IAS)", which aims to measure subjective anxiousness in specific social situations, by investigating the individual's tendency to feel nervous in social encounters, independently of patterns of inhibited, reticent, or avoidant behaviour. Hence, IAS considers only the affective component of social discomfort (Leary and Kowalski 1993), differently from other instruments which in turn focus on cognitive aspects of the phenomenon, such as the "Fear of Negative Evaluation Scale" (Watson and Friend 1969) and the "Social Interaction Self-statement Test" (Glass et al. 1982), or both affective and behavioural facets, such as the "Social Avoidance and Distress Scale" (Watson and Friend 1969) and Liebowitz Social Anxiety Scale (Liebowitz 1987).

The IAS is composed by 15 items referring to subjective affective reactions to social situations, such as feeling "anxious," "nervous," and "tense", whereas there are no mentions to specific social behaviours, such as avoidance of interactions, a hesitancy to speak to others, etc. Respondents indicate how much the experience described in the sentence is characteristic of them when they interact with other people. The IAS seems to represent a valid instrument to measure the presence of social anxiousness among youths across different interactions scenarios. For instance, having a conversation with a person of the opposite sex, meeting new people in a party or talking with authority figures (e.g. teachers), all situations which seems to be near to adolescents' social experience.

The instrument revealed a one-factor structure in its final 15-items version developed among American university students (Leary 1983). Leary and Kowalski (1993) have collected extensive data on the psychometric properties of the scale, revealing a high test-retest and internal reliability (respectively of 0.80 and 0.85) as well as good construct and criterion-related validity. More specifically, IAS showed high correlations with other measures of social anxiety, inhibition, and shyness, such as the SAD Scale (Watson and Friend 1969), the Shyness Scale (Cheek and Buss 1981), the Social Anxiety subscale of the Self-Consciousness Scale (Fenigstein et al. 1975), moderate (range = 0.35–0.50) with measures of specific subtypes of social anxiety (e.g., physique anxiety, embarrassability), as well as general anxiety (e.g., neuroticism, trait anxiety), and low ($r = -0.26$) with Marlowe-Crowne Social Desirability Scale (Crowne and Marlowe 1964), giving some evidences of discriminant validity (Leary 2013).

Respect to the European context, a study conducted with Spanish university students (Sanz 1994) on IAS psychometrics proprieties found high reliability (Cronbach $\alpha = 0.90$), high and positive correlation with the SAD scale ($r = 0.76$), and an acceptable discriminant validity with respect to depression measured by the Beck Depression Inventory (Beck et al. 1996) ($r = 0.43$). In the same Spanish study, data concerning factorial validity for the IAS consistently indicate either the existence of only one factor or the existence of two highly related factors: a large general social anxiousness factor on which most of the items would load, and a small factor on which items related to interaction with authority figures, as emerged also in a study among American university students (Leary and Kowalski 1986).

A study conducted among Turkish adolescents (Subasi 2013) with a 21-items version of the IAS adapted to Turkish young population by Subasi (2007) revealed a high internal consistency (Cronbach $\alpha = 0.86$) and a high split-half reliability (Spearman–Brown and Guttman's reliability coefficients were also calculated and found to be .85 for both). For the construct validity of scale, a factor analysis was run, and it was observed that the scale revealed a unidimensional solution. Unfortunately, there is not an Italian validation of IAS, although some studies employ the instrument, especially among young people (Contardi et al. 2013; De Berardis et al. 2007). In the Italian context, instruments for the investigation of social anxiety among adolescents in turn focus on shyness ("Children's Shyness Questionnaire" ; Spensieri et al. 2019), appearance anxiety ("Social Appearance Anxiety" ; Dakanalis et al. 2016) and social phobia ("Social Anxiety Questionnaire for Children" ; Caballo et al. 2012; "Social Phobia and Anxiety Inventory for Children" ; Ogliari et al. 2011); to date, no instrument specifically investigate on the adolescent's social anxiety by recalling what he/she feels in different social interactions. Yet, interacting with peers, authorities, strangers, and the opposite sex are all scenarios which require to manage the impression on others, a matter of great concern during the adolescence more than in other periods (Johnson et al. 2011); furthermore, the individual's self-image—strictly connected to social anxiety (Di Blasi et al. 2015)—includes also perceptions about one's own social attitudes (Offer et al. 1989) which organize the functioning in various social domains, which are specifically investigated by the IAT.

Having an instrument of social anxiety addressed to young people seems very important in the field of mental health. Adolescence is known to be a period of great changes in the social sphere, with an increasingly openness to the world of peers, to whom they become more reliant (Larson and Richards 1994); unsurprisingly, social anxiety may climb with the transition to this period of life, as reported in several empirical studies (Costello et al. 2003; Michiel Westenberg et al. 2004; Wittchen et al. 1999). In the social context of peers, where they spend more time, exercise their social skills, and have new experiences in intimacy and sexuality (Buhrmester and Furman 1987; Larson and Richards 1994), adolescents face with strong desires for personal validation and consequently with the fear of negative evaluation and rejection (Harter et al. 1996; Leigh and Clark 2018; McElhaney et al. 2008). Adolescents high in social anxiety may in turn manifest other problems, such as depression (Beesdo et al. 2007; Stein et al. 2001), suicide (Davidson et al. 2011; Gallagher et al. 2014), substance abuse (Buckner et al. 2008, 2007), problematic internet use (Caplan 2006; Lee and Stapinski 2012; Venuleo et al. 2020), poor school performance (Mazzone et al. 2007; Van Ameringen et al. 2003).

The present study addresses the following objective:

1. to examined the factor structure and model specifications of the Interaction Anxiousness Scale (IAS) with confirmatory composite analysis (CCA) PLS approach, that is to evaluate the presence of eventual sub-scales specific of Italian adolescents;

2. to test the measurement model of IAS with Italian adolescents using a higher-order modeling, that is modeling the concept of social anxiousness on a more abstract dimension (referred as higher-order component) and its more concrete sub-dimensions (i.e. lower-order components) linked by reflective relationships.

2 Method: data analysis

The scale has evaluated following a two stages of analysis: The first stage is an explorative analysis, aimed at investigate the latent structure underlying the IAS scale to evaluate the presence of eventual sub-scales specific of the sample analysed; in the second stage, the sub-scales identified will be confirmed by using a new/recent method called CCA based on PLS-PM. As suggested by Hair et al. (2019), the two stages are performed by randomly dividing the sample in two sub-samples of 382 units each: A training sample where the explorative analysis is executed; a test sample where the CCA is conducted for the confirmatory purpose. In the following sub-sections an in deep focus on the methodologies and their use will be illustrated.

2.1 Explorative analysis (PCA)

To ascertain the number of dimensions contained in the IAS scale, data were subjected to a principal component analysis (PCA), a multivariate analysis technique aimed to explain the variability of a phenomenon in a way that preserves as much 'variability' (i.e. statistical information) as possible, that is, reducing the dimensionality of a dataset with observations on p numerical variables, using a q number of components so that $q < p$ (Jolliffe and Cadima 2016). This analysis was run on R software. Before executing the confirmative analysis with CCA, PCA was used for exploring the theoretical and latent structure of the scale, in way to highlight sub-scales in the IAS. More specifically, a sequence of analyses was performed on the whole items, considering orthogonal rotations, in way to select and remove the groups of items with high saturation coefficients, with the aim to identify new latent constructs (sub-scales), according to a theoretical background.

2.2 Confirmatory composite analysis for higher-order modelling with PLS

To confirm the factorial structure a partial least squares-path model (PLS-PM) with higher-order construct has been implemented and evaluated by using a confirmatory composite analysis (CCA) trough SmartPLS and R software. CCA can be seen as an emergent and systematic method/process for confirming the measurement model in the partial least squares framework for the structural equation modelling (Hair et al. 2019; Henseler et al. 2016; Hair et al. 2019; Schuberth et al. 2018).

2.2.1 The higher order modelling

The IAS has been conceptualized as a second order latent variable based on the explorative analysis made in the first step. The advantage of higher-order construct (HOC) can be seen from both theoretical and empirical considerations (Cheah et al. 2019; Sarstedt et al. 2019; Ciavolino and Nitti 2013a, b).

A higher-order construct allows researchers to be able to model a concept on a more abstract dimension (referred to as a higher-order component) and its more concrete sub-dimensions (i.e. lower-order components).

Moreover, by using a higher-order construct, it able to obtain parsimony in a model because the modelling helps to reduce the number of relations of the path model (Johnson et al. 2011; Polites et al. 2012). In other words, it helps to overcome the bandwidth-fidelity dilemma (Cronbach and Gleser 1957) and it can deal with multicollinearity matter, especially for the case of formative indicators (Hair et al. 2018).

Higher-order models can be estimated by using MLE and PLS methods, but they are usually referred to the PLS framework under the name of hierarchical component models, especially for the various procedures to define the hierarchical structure (repeated indicators, two stage, hybrid) in the variables and the methods to define the relationships between higher and lower order variables (reflective and formative, see Cheah et al. 2019; Sarstedt et al. 2019).

Wold's original design of PLS path modelling does not consider higher-order latent variables, but in the last years several approaches has been proposed to estimate Higher-Order Latent Variables in PLS-SEM: (1) the repeated indicator approach and the extended version (Wold 1982; Lohmöller 1998; Becker et al. 2012; 2) the sequential latent variable score method or two-stage approach (Becker et al. 2012; Nitti and Ciavolino 2014; Wetzels et al. 2009; Ringle et al. 2012); (3) the hybrid approach (Bradley and Henseler 2007) and (4) the recent approach aimed at using Mode A consistent (or PLSc) estimation that assess HCM as composites of common factors (Van Riel et al. 2017).

2.2.2 Measurement model: why reflective-reflective (Type I)?

The use of a higher order constructs implies that researchers must ensure that the measurement theory is well developed and the higher-order construct's conceptualization and specification must be based on this. In the literature there are four types of HOCs (Becker et al. 2012; Cheah et al. 2019; Ringle et al. 2012):

1. reflective-reflective, that implies a type of reflective relationship between the HOC and the lower order constructs (LOCs) and where the latter are also measured in a reflective way;
2. reflective-formative, where the HOC represents a more general construct of the reflectively measured LOCs. The specific LOCs do not necessarily share a common cause but rather form the general HOC. This model is employed when a modification in one dimension does not necessarily imply a modification in

another, so they do not necessarily co-vary. Rather, each dimension can vary independently of the others (Barroso and Picón 2012);

3. formative-reflective, that includes a more general HOC that explains the formatively measured LOCs. As goal there is the extracting of the common part of formatively measured LOCs, that represent the same theoretical content. However, every LOC builds on a set of different indicators.

4. formative-formative, an HCM that determines the relative contribution of the formatively measured LOCs to the more abstract HOC. The purpose of this model is to structure a complex formative construct with many indicators into several sub-constructs, as is the case when researchers subsume several concrete aspects under a more general concept.

In our contribution, the choice of the reflective-reflective model implies a type of reflective relationship between the HOC (IAS) and the LOCs (based on the results of the PCA Analysis), where the latter are also measured in a reflective way. The graphical representation of the reflective-reflective model is conceived with arrows/relationships start from the HOCs reaching the LOCs and then, with arrows from the LOCs to the MVs (items).

The reason that makes the choice of the reflective-reflective model appropriate lies in the high correlation of the LOCs , in which the HOC is the common factor of many other specific lower factors (LOCs), and the main objective of this study is to derive distinct reflective LOCs (Becker et al. 2012; Lohmöller 1998) having an HOC as common factor.

The decision of the reflective-reflective model is also supported by the (soft) psychological theory at the base (analyzed in deep by the PCA in the first step) since it is the presence of a certain level of anxiety in the adolescent's social interactions that gives rise to discomfort and sense of inadequacy in interactions, nervousness when interacting with authority figures, discomfort in unstructured interactions or to comfortability in interaction with unknown—the latter when such level is lower.

2.2.3 Estimation methods

Two main approaches in estimating SEM parameters have raised two important issues: the first concerns the parametric approach, with the maximum likelihood estimation (MLE) method developed by Jöreskog (1970); the second one concerns a nonparametric approach, namely partial least squares (PLS) by Wold (1975). In the last years also some news estimation approaches have been proposed and used in literature as the generalized structured component analysis (Hwang and Takane 2004) and the generalized maximum entropy (GME) as semi-parametric approach (Ciavolino and Al-Nasser 2009; Ciavolino and Dahlgaard 2009; Carpita and Ciavolino 2017).

For a sake of simplicity here we give a little introduction to MLE and PLS that represent the two mainstream methods and in deep discussed from theoretical and applied point of view, with the aim to motive the choice of PLS approach. The parametric approach MLE (Jöreskog 1970) also known as covariance-based SEM has

been conceptualized as the hard modeling with distribution assumptions, big sample size and some limits in the specification of formative indicators. The non-parametric approach PLS also known as component based SEM, PLS-SEM or PLS-PM, has been proposed by Wold (1975) and defined as soft modeling and in contrast with MLE do not require distributional assumptions, there are no identification problem, it works with small sample size and it is easy to define reflective and formative items. Research has gradually led to the shift from targeted and simple models to more complex models (Sharma et al. 2019) with higher-order constructs (Sarstedt et al. 2019) and this transition is also mainly due to the greater diffusion of PLS estimator in the SEM framework.

In this this study, PLS approach was used because it avoids hypotheses on data distribution (see Sect. 3.1) and sample size and not tests the model by evaluating discrepancies between empirical and implicit covariances of the model (Hair et al. 2016, 2017; Vinzi et al. 2010; Rigdon et al. 2017). Moreover, PLS-SEM can determine unique score for the constructs (Rigdon 2016), so it is more appropriate for scale development and assessment. Finally, PLS-SEM does not require an underlying theoretical model before data collection, unlike CB-SEM.

2.2.4 Confirmatory composite analysis

A recent method for confirming and evaluating the measurement models in PLS-SEM is the so called CCA (Henseler et al. 2014). This approach can be seen as a non-parametric version of the confirmative factorial analysis with the adoption of the terminology "composites" (Rigdon 2014) to make clearer PLS-SEM applications and terminology.

The statistical objective of CCA is the confirmation of a measurement theory and begin with proposing theoretical constructs to be confirmed (Hair et al. 2020).

To assess the higher-order measurement model a two-stage process has to be followed as showed in the Fig. 1: in the first stage, the lower order measurement model is assessed considering the standard steps; in the second stage the HOC is assessed by considering as items the LOCs leaving out the repeated items.

The Fig. 1 is specific for the presented case study and therefore for the reflective-reflective measurement model, but it can be generalized for the four types of HOCs (Becker et al. 2012; Cheah et al. 2019; Ringle et al. 2012) as specified above. Below there are the steps should be followed to execute a CCA with reflective-reflective measurement models split in two stages defined above:

Stage 1: LOC measurement model assessment:

– (1) The first step to follow is the *assessment of the indicator loadings and their significance*, obtaining a value between 0.40 and 0.708 for the standardized loadings (Hulland 1999). Through bootstrapping procedure (Hair et al. 2012) associated t-statistic should be above ±1.96 to be significant for a two-tailed test at the 5% level (Hair et al. 2012);
– (2) The second step regarding the indicators reliability (items), that is the quantity of the amount of variance, shared between the individual indicator variable
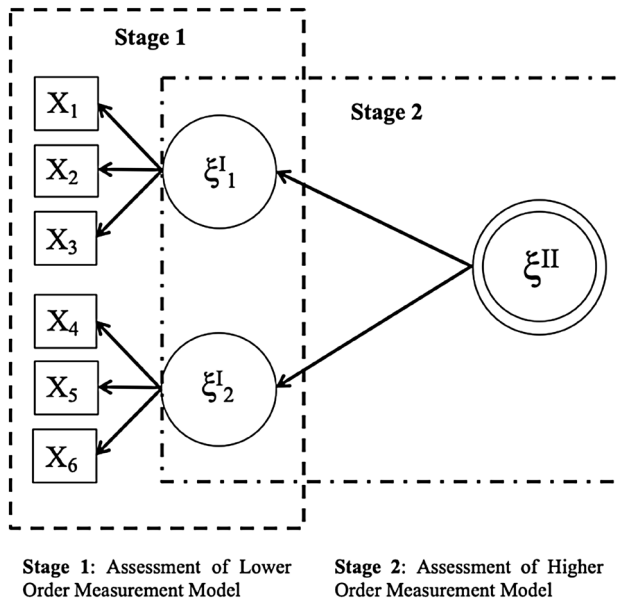
Stage 1: Assessment of Lower Order Measurement Model   **Stage 2**: Assessment of Higher Order Measurement Model

Fig. 1 CCA assessment stages for higher-order model

and its associated construct, is provided by squared individual indicator loadings (Hair et al. 2019);

– (3) In the third step for the composite reliability (construct) assessment the two reliability criteria Cronbach's alpha (α) and composite reliability (CR) can be employed and both need a value above 0.70. The unweighted Cronbach's alpha is more precise than composite reliability (that is weighted), because indicators are not equally reliable;

– (4) In the fourth step convergent validity is measured by the average variance extracted (AVE), obtained by averaging the indicator reliabilities of a construct, which value must be equal to/exceed the 0.50 threshold;

– (5) Discriminant validity was assessed using three criteria including cross-loadings, Forner–Lacker criterion (Fornell and Larcker 1981), and heterotrait-monotrait (HTMT) as suggested by Henseler et al. (2015), Hair et al. (2017). The first method provides that the outer loading of an item should be greater on its respective latent variable than its cross-loadings on other latent variables. According to Forner–Lacker criterion, the square root of AVE, of each of the latent variable, should be greater than its correlation with other latent variables. In the end, HTMT approach can be seen as an estimation of the inter-construct correlation (Nunnally 1978; Netemeyer et al. 2003), that in case has a value close to 1 shows a non-discrimination between constructs. HTMT can be used as criterion, with a thresholds of 0.85 (Kline 2011; Clark and Watson 2016) and 0.90 (Gold et al. 2001; Teo et al. 2008), or as bootstrap statistical test (*HTMT_inference*), defining confidence intervals: if the value one is contained in CI, the two components are not empirically distinct, while if one is outside of the intervals,

this suggests no discriminant validity problems. (Shaffer 1995; Henseler et al. 2015).

Stage 2: HOC measurement model assessment:

– (1) Reliability: the composite reliability is defined as:

$$\rho_c = \frac{(\sum_{k=i}^{p} l_i)^2}{(\sum_{k=i}^{p} l_i)^2 + \sum_{k=i}^{p} \text{var}(e)_i} \tag{1}$$

where p is the number of LOCs, $(e)_i$ and $\text{var}(e)_i$ are respectively the measurement error and its variance of the ith LOC, (note that $(e)_i = 1 - l_i^2$). Since the repeated indicator is estimated by the using a standard PLS-SEM approach, the estimated l_l coincides with the estimated path coefficients between HOC and LOCs. The Cronbach's alpha is defined as follow:

$$\alpha = \frac{p \cdot \bar{r}}{1 + (p - 1) \cdot \bar{r}} \tag{2}$$

where $\bar{r}$ is the average of the correlations between the LOCs.
– (2) Convergent validity: assessed by the AVE index, is the average of the HOC's squared loadings l_i^2 (squared beta coefficients) between HOC and LOCs:

$$\text{AVE} = \frac{\sum_{k=i}^{p} l_i^2}{p} \tag{3}$$

– (3) Discriminant validity is based on the same criteria defined above for the LOCs: cross-loadings, Forner–Lacker and HTMT. In the HOC measurement model the assessment of discriminant validity has to be performed by considering components in a nomological/legal network, that means the HOC has to be linked to any other exogenous or endogenous variable. In our specific case study, the HOC is specified as a stand-alone component, so it does not make sense to evaluate the discriminant validity.
– (4) Assessing the LOCs loadings and their significance: In the second stage it is important to remember that also the statistical significance has to be evaluated by bootstrap method.

3 Results

3.1 Sample description

The dataset used in this study was obtained from a larger web-based survey on adolescents' well-being and risk behaviors. The study was performed in public high schools situated in the Southern Italy with a total of 764 high school pupils attending year 9 (52%) and 11 (48%) and aged from 13 to 19 (mean age= 15.05 ± 1.152), among whom 46.9% were female.

Written parental consent was required through the participating schools some days before the administration; the students have filled the questionnaire on their classroom PCs using Google Forms. It was outlined the voluntary nature of the participation and the anonymity of the responses and encouraged questions for any doubts and needs of clarification. The socio-demographic characteristics of the sample, disaggregated for gender, are shown in Table 1 no significant differences related to gender have been found.

Moreover, the Shapiro-Wilk's test is performed per each IAS variable and all the items showed a p value < 0.05, implying that the sample is significantly different from normal distribution. Multivariate normality was not performed because univariate normality is a condition needed to evaluate for it (Mvududu and Sink 2013).

3.2 Instrument and procedures

The Interaction Anxiousness Scale (IAS; Leary 1983) is a self-report questionnaire composed by 15 items and scores on 5 points Likert (from 1 = "Not at all" to 5 = "Extremely"). Item 8 was adapted to the age of the sample, therefore changed from "I would be nervous if I was being interviewed for a job" to "I would be nervous if I had an oral test" . The total score is obtained by summing the responses to each items, after reversing the items 2, 3, 6, 10 and 15. IAS scores ranges from 15 to 75, with high scores indicating a high level of social anxiety in interactional situations. In the present study, the Italian translation of the instrument was developed through a back-translation method (see Appendix).

3.3 PCA results

A sequence of three PCAs, considering orthogonal rotations, was performed on the training sample ($n = 382$) considering all the items of IAS construct: in each PCA, when a group of items saturated on a component and this set of indicators made sense with respect to the psychological theory, these indicators were removed and the number of components decreased by one. Below the results of every PCAs, with the relative items and the eigenvalues:

Table 1 Socio-demographic characteristics of the sample

	Male (%)	Female (%)	Total (%)	Chi-square
Age				
13–15	54.1	45.9	427	0.356
16–19	51.9	48.1	337	
Class				
Year 9	53.4	64.6	397	0.022
Year 11	52.9	47.1	367	

- First PCA with four components fixed, the results confirm the presence of a component on which items 2, 3 and 15 saturate (first eigenvalue = 3.561; second eigenvalue = 1.443);
- Second PCA having 3 components fixed, the items 9, 11, 12 and 13 saturate on the same factor (first eigenvalue = 3.414; second eigenvalue = 1.066)
- Third PCA it reveals another a component on which item 8, 4 and 14 saturate (first eigenvalue = 2.106; second eigenvalue = 0.934) and another component on which the remaining item 1, 5 and 7 saturate.

These analyses revealed a four-factor solution. Table 2 reports the correlations between the items and the four components: (1) Component 1: item 2, item 3, item 15 (ξ^I_{IAS1}); (2) Component 2: item 9, item 11, item 12, item 13 (ξ^I_{IAS2}); (3) Component 3: item 4, item 8, item 14 (ξ^I_{IAS3}); (4) Component 4: item 1, item 5, item 7 (ξ^I_{IAS4}).

The formalization of the theoretical model is defined by the path diagram reported in the following Fig. 2.

Table 3 shows the main descriptive statistics on the whole sample (mean, SD mean, SD, skewness, SE skewness, kurtosis and SE kurtosis) for all items. In the first column, the main component on which each MV saturates (i.e. a summary of the PCAs performed).

The first factor (ξ^I_{IAS1}) consists of items (i.e. positively worded items, to be reversed) referring to Comfortability in interactions with unknown other; the second (ξ^I_{IAS2}) to discomfort and sense of inadequacy in interactions; the third (ξ^I_{IAS3}) to Nervousness in interactions with authority; the forth (ξ^I_{IAS4}) to discomfort in unstructured interactions.

Table 2 Saturation matrix

	PCA 1	PCA 2	PCA 3	
Items	1	2	3	4
IAS2R	0.619			
IAS3R	0.514			
IAS15R	0.611			
IAS9		0.662		
IAS11		0.625		
IAS12		0.655		
IAS13		0.668		
IAS4			0.698	
IAS8			0.660	
IAS14			0.500	
IAS1				0.612
IAS5				0.508
IAS7				0.550

'None' rotation was used

3.4 CCA results

CCA analysis was performed on SmartPLS software version 3.33 (Ringle et al. 2015) and underneath are shown the two stages for the HOC and LOCs and the steps followed for the reflective-reflective measurement model:

Stage 1 LOC measurement model assessment:

– Step (1) Assessing the indicator loadings and their significance: In Table 4, all the standardized loadings have a value greater than 0.5 and the associated boot-strap T-statistics reveal them significant. According to Hair et al. (2018) stated that in exploratory case, loading can be 0.4 as long as AVE met the minimum threshold value of 0.5 (Hair et al. 2019);
– Step (2) Indicators reliability (items): All the squared individual indicator load-ings (reported in Table 4 above) provides a good measure of the amount of vari-ance shared between each single item and the component on which it saturates;
– Step (3) Composite reliability (construct): This index values are more than acceptable, because the CR values for each LOCs are respectively equal to 0.762, 0.809, 0.753, 0.773 and therefore greater than the threshold of 0.700. In this case, composite reliability (weighted) is more accurate than Cronbach's alpha (unweighted), because indicators are not equally reliable (see Table 5). Moreo-ver, the last two columns show the uni-dimensionality of the sub-scales;
– Step (4) Convergent validity: The average variance extracted (AVE) values, being equal to/exceed the 0.50 threshold for all the LOCs (respectively, AVE = 0.517, 0.515, 0.512, 0.532) are more than acceptable (see Table 5);
– Step (5) Discriminant validity: The Table 6 shows outer loadings (in bold) between the items and correspondent component greater than the cross-load-ings with any other component. Forner–Lacker criterion is also satisfied, since
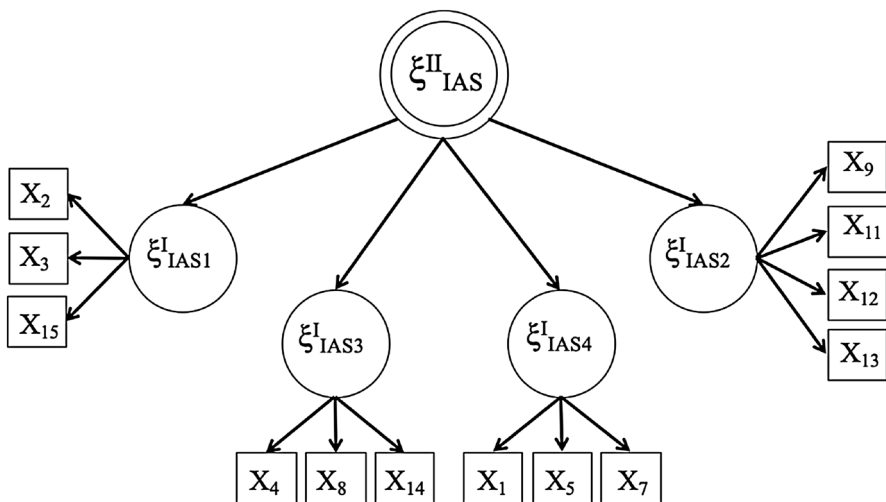

Fig. 2 Theoretical path model

Table 3 Interaction anxiousness scale items: descriptive statistics

Item description	Factor	Mean	SE mean	SD	Skewness	SE skewness	Kurtosis	SE kurtosis
2. I usually feel comfortable when I'm in a group of people I don't know	1	3.61	0.0402	1.11	−0.350	0.0884	−0.686	0.177
3. I am usually at ease when speaking to a member of the other sex	1	2.31	0.0390	1.08	0.752	0.0884	0.110	0.177
15. I usually feel relaxed around other people, even people who are quite different from me	1	−2.99	0.0417	1.15	0.0592	0.0884	−0.804	0.177
9. I wish I had more confidence in social situations	2	2.72	0.0448	1.24	0.323	0.0884	−0.932	0.177
11. In general, I am a shy person	2	2.34	0.0441	1.22	0.632	0.0884	−0.606	0.177
12. I often feel nervous when talking to an attractive member of the opposite sex	2	2.57	0.0448	1.24	0.417	0.0884	−0.871	0.177
13. I often feel nervous when calling someone I don't know very well on the telephone	2	2.20	0.0397	1.10	0.795	0.0884	−0.0558	0.177
4. I get nervous when I must talk to a teacher or a boss	3	2.29	0.0406	1.12	0.614	0.0884	−0.389	0.177
8. I would be nervous if I had an oral test	3	2.94	0.0446	1.23	0.185	0.0884	−1.03	0.177
14. I get nervous when I speak to someone in a position of authority	3	2.35	0.0455	1.26	0.626	0.0884	−0.700	0.177
1. I often feel nervous even in casual get-togethers	4	1.98	0.0345	0.953	0.901	0.0884	0.489	0.177
5. Parties often make me feel anxious and uncomfortable	4	1.65	0.0354	0.977	1.59	0.0884	2.04	0.177
7. I sometimes feel tense when talking to people of my own sex if I don't know them very well	4	1.88	0.0349	0.965	0.980	0.0884	0.465	0.177

Items 6 and 10 has been removed; for Italian translation see the Appendix

Table 4 Indicators loadings and confidence intervals

Relationship	Original sample	Sample mean	SD	Confidence intervals	T statistics	p values
$\xi^I_{IAS1} \rightarrow IAS2R$	0.738	0.736	0.067	[0.630; 0.851]	10.953	0.000
$\xi^I_{IAS1} \rightarrow IAS3R$	0.749	0.743	0.054	[0.666; 0.845]	3.757	0.000
$\xi^I_{IAS1} \rightarrow IAS15R$	0.667	0.658	0.085	[0.535; 0.815]	7.840	0.000
$\xi^I_{IAS2} \rightarrow IAS9$	0.710	0.710	0.036	[0.652; 0.769]	19.976	0.000
$\xi^I_{IAS2} \rightarrow IAS11$	0.770	0.770	0.025	[0.730; 0.812]	31.031	0.000
$\xi^I_{IAS2} \rightarrow IAS12$	0.703	0.702	0.031	[0.652; 0.755]	22.480	0.000
$\xi^I_{IAS2} \rightarrow IAS13$	0.684	0.684	0.037	[0.624; 0.746]	18.449	0.000
$\xi^I_{IAS3} \rightarrow IAS4$	0.761	0.760	0.040	[0.697; 0.828]	19.114	0.000
$\xi^I_{IAS3} \rightarrow IAS8$	0.819	0.817	0.030	[0.771; 0.870]	27.041	0.000
$\xi^I_{IAS3} \rightarrow IAS14$	0.535	0.533	0.073	[0.417; 0.658]	7.314	0.000
$\xi^I_{IAS4} \rightarrow IAS1$	0.732	0.731	0.034	[0.676; 0.789]	21.403	0.000
$\xi^I_{IAS4} \rightarrow IAS5$	0.708	0.706	0.042	[0.641; 0.780]	16.695	0.000
$\xi^I_{IAS4} \rightarrow IAS7$	0.749	0.748	0.034	[0.693; 0.806]	21.865	0.000

the square root of AVE of each component is greater than its correlation with other components (see Table 7). In the end, Table 8 reports the HTMT values and the bootstrap confidence interval in the parentheses. All the values are below the threshold of 0.85, showing a a good distinctiveness, with the only exception of the components ξ^I_{IAS2} and ξ^I_{IAS4}. Still this relationship, since in a scale development and exploratory point of view (Henseler et al. 2015), can be analyzed taking into account the bootstrap HTMT$_{inference}$ confidence interval, that reveals empirically distinct components, since the value 1 is not included in. The discriminant validity between the four composites and their higher-order component ξ^{II}_{IAS} it is not relevant. An incorrect value of discriminant validity between these constructs is expected, because the measurement model of the higher-order component repeats the indicators of its four lower-order components.

Table 5 Reliability and convergent validity

	MVs	CR (ρ_c)	AVE	Eig. 1	Eig.2
ξ^I_{IAS1}	3	0.762	0.517	3.561	1.443
ξ^I_{IAS2}	4	0.809	0.515	3.414	1.066
ξ^I_{IAS3}	3	0.753	0.512	2.106	0.934
ξ^I_{IAS4}	3	0.773	0.532	1.424	0.804

Table 6 Crossloading

	ξ^I_{IAS1}	ξ^I_{IAS2}	ξ^I_{IAS3}	ξ^I_{IAS4}
IAS2R	**0.738**	0.212	0.144	0.099
IAS3R	**0.749**	0.207	-0.004	0.138
IAS15R	**0.667**	0.183	-0.058	0.148
IAS9	0.192	**0.710**	0.282	0.459
IAS11	0.332	**0.770**	0.324	0.452
IAS12	0.169	**0.703**	0.364	0.401
IAS13	0.091	**0.684**	0.360	0.390
IAS8	0.054	0.376	**0.819**	0.198
IAS4	0.036	0.337	**0.761**	0.169
IAS14	0.006	0.270	**0.535**	0.093
IAS1	0.146	0.413	0.166	**0.732**
IAS5	0.122	0.412	0.057	**0.708**
IAS7	0.118	0.471	0.248	**0.749**

Table 7 Fornell–Larcker criterion

	ξ^I_{IAS1}	ξ^I_{IAS2}	ξ^I_{IAS3}	ξ^I_{IAS4}
ξ^I_{IAS1}	0.719			
ξ^I_{IAS2}	0.280	0.718		
ξ^I_{IAS3}	0.048	0.462	0.716	
ξ^I_{IAS4}	0.176	0.594	0.222	0.730

Table 8 HTMT matrix and confidence intervals

	ξ^I_{IAS1}	ξ^I_{IAS2}	ξ^I_{IAS3}
ξ^I_{IAS2}	0.459 [0.330; 0.588]		
ξ^I_{IAS3}	0.259 [0.157; 0.361]	0.784 [0.660; 0.908]	
ξ^I_{IAS4}	0.332 [0.186; 0.479]	0.921 [0.865; 0.976]	0.394 [0.263; 0.526]

Stage 2: HOC measurement model assessment:

– Step (1): Reliability: The composite reliability being equal to 0.781, provides clear support for the higher-order construct's internal consistency reliability, because it exceeds the threshold of 0.7;
– Step (2): Convergent validity: AVE index is $(0.412^2 + 0.919^2 + 0.606^2 + 0.762^2)/4 = 0.491$, with a bootstrap confidence interval [0.419; 0.572]. Convergent validity is still acceptable since confidence interval includes 0.5 and also, as suggested by Fornell and Larcker (1981), even low of 0.5, the composite reliability is higher than 0.6;

– Step (3): Discriminant validity. For the proposed model, discriminant validity can not be evaluated, since the HOC is not a nomological network;

– Step (4): Assessing the LOCs loadings and their significance: Then, it is important to analyze the structural model using bootstrapping method with 300 subsamples and found that all structural model relationships are significant ($p < 0.05$) (see Table 9). The explained variance of the HOC is mainly due to ξ^I_{IAS2} (0.919) followed by ξ^I_{IAS4} (0.762), ξ^I_{IAS3} (0.606) and in the end by ξ^I_{IAS1} (0.412). After these assessment stages, it is possible to confirm that the IAS scale, through CCA, reveals a structure with four composites/factors. Based on this notion, IAS can be conceptualized as a higher-order construct comprising the four lower-order components ξ^I_{IAS1}, ξ^I_{IAS2}, ξ^I_{IAS3} and ξ^I_{IAS4}, as reported in the Fig. 3. In particular, ξ^I_{IAS1} is made up of items (measurable variables) 2, 3 and 15; ξ^I_{IAS2} from items 9, 11, 12 and 13, ξ^I_{IAS3} from items 4, 8 and 14, while ξ^I_{IAS4} from items 1, 5 and 7.

4 Discussion

The results indicate a four-factors structure of the IAS for Italian adolescents. Through the use of CCA, we find support to the appropriateness of a reflective-reflective IAS measurement model; more precisely, IAS is best conceptualized as a second-order reflective-reflective measurement model. To our knowledge, this is the first study to evaluate the appropriateness of the IAS and to assess its factor structure using a higher-order modelling method.

Based on conceptual, pragmatic, and statistical evidence, our innovative second-order reflective-reflective IAS measurement model asserts that the presence of a certain level of anxiety in the adolescent's social interactions gives rise to discomfort and sense of inadequacy in interactions, nervousness when interacting with authority figures, discomfort in unstructured interactions or to comfortability in interactions with unknown other—when the levels of social anxiety are lower.

More specifically, respect to the first factor (ξ^I_{IAS1}) "comfortability in interactions with Unknown Other" , the anxious adolescent reports low positive subjective experiences—such as feeling comfortable and relaxed—in a group of people he/she does not know, a conversation with someone of the opposite sex, and among people different from him/her. A similar finding can be traced in a study by Myers et al. (2002) which identified novel social situation fears (e.g. being surrounded by unknown

Table 9 Higher-order measurement model (structural model estimates)

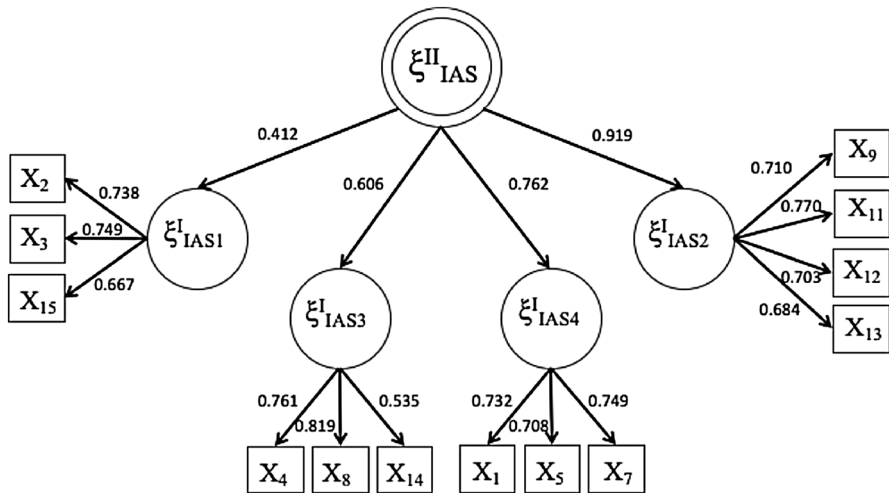| Relationship	Original sample	Sample mean	SD	Confidence intervals	T statistics	p values
$\xi^{II}_{IAS} \to \xi^I_{IAS1}$	0.412	0.418	0.077	[0.280 ; 0.532]	5.377	0.000
$\xi^{II}_{IAS} \to \xi^I_{IAS2}$	0.919	0.919	0.010	[0.904; 0.936]	92.187	0.000
$\xi^{II}_{IAS} \to \xi^I_{IAS3}$	0.606	0.609	0.054	[0.514 ; 0.693]	11.174	0.000
$\xi^{II}_{IAS} \to \xi^I_{IAS4}$	0.762	0.762	0.026	[0.718 ; 0.804]	29.106	0.000

Fig. 3 Path model with the estimated parameters

people) as a sub-dimension of adolescents social anxiety. The second factor (ξ^I_{IAS2}) "discomfort and sense of inadequacy in interactions" consists of items describing lack of self-confidence, shyness, and nervousness in various interactive scenarios: in this case, the presence of social anxiety rises feelings of inadequacy, namely feeling and seeing oneself as incompetent to cope with social situations, inferior and unattractive—well-recognized signs of social anxiety also by other scholars (e.g. Iwase et al. (2000); Matos et al. (2013)). The factor (ξ^I_{IAS3}) "nervousness when interacting with authority" identifies difficulties in conversations with teachers, boss, and authority figures as well as in oral text: the fear of authority is indeed often reported by adolescents high in social anxiety (Garcia-Lopez et al. 2008; Ranta et al. 2007). Finally, the fourth factor (ξ^I_{IAS4}) "discomfort in unstructured interactions" refers to negative subjective experiences in situations such as parties, causal encounters, and interactions with unknown peers of one's own sex: although such interactions can be considered common in adolescence due to a major social exploration, they may rise nervousness in social anxious adolescents since their unstructured nature, that is a higher unpredictability (Clauss et al. 2019; Smith et al. 2020).

Conceptually, it seems useful to have an instrument which offers different social scenarios, recalling the subjective experience associated with them. These subjective experiences can be in turn connected to the subject's self-image—very salient during adolescence (Erikson 1968; Di Blasi et al. 2015)—namely if he/she perceives him/herself alternatively as an uneasy or a confident social actor. Therefore, as pointed out by the existence of the 1st factor (ξ^I_{IAS1}), an adolescent who feel comfortable in social situations—i.e. who perceives him/herself as a proper social actor—does not seem scared to interact with someone who can be defined Unknown, namely of the opposite sex, different from her/his, or unknown. On the contrary, social anxious adolescents are too much worried about the first impression given to people they do not know (Cannon et al. 2020; Glenn et al. 2019) as well as in heterosocial

encounters (Asher and Aderka 2020; La Greca and Harrison 2005). Consistently, as highlighted by the 2nd factor (ξ_{IAS2}^I), they report discomfort in social situations in general as well as in interactions with someone unknown who cannot be seen (i.e. in interactions through the phone) or who belongs to the opposite sex (i.e. someone attractive): all this scenarios suggest that social anxiety enhance their sense of inadequacy which is associated with shyness, lacking of confidence (Weeks et al. 2016) as well as difficulties when interacting with someone appealing (Leary and Jongman-Sereno 2014) or a stranger by voice (Reid and Reid 2007). In the case of the 4th factor (ξ_{IAS4}^I), the adolescent-social actor high in social anxiety feels discomfort in unstructured interactions, namely situations to handle with unclear expectations such as parties and new encounters (Glenn et al. 2019; Hofmann et al. 1999). Respect to the interactions with authorities collected in the third dimension (ξ_{IAS4}^I), it is possible to interpret such finding considering that figures in a position of authority are particularly problematic for social anxious people (Leary and Kowalski 1986; Mehtalia and Vankar 2004) especially adolescents may have many concerns regarding the way in which they were evaluated by their teachers and similar, because during this stage of age they are facing for other authority figures beyond their parents.

Another aspect that has to be considered is that although the original version of the instrument developed by Leary (1983) among American university students has a one-factor structure, our results indicate the existence of four factors. A study in the European context (i.e. Spain) among people aged from 20 to 41 years old has found either a one-factor and a two-factors structure, the latter with a small second factor related to interactions with authorities (e. g., professor, boss), suggesting that social anxious individual are particularly sensitive to evaluations from people in an authority position, as also emerged from our sample. Differences in the factorial structure could depend firstly on the innovative statistical method of investigating the factorial structure, as mentioned above; furthermore, it could mean that the phenomenon studied in the target culture has peculiar characteristics, so that the different factorial structures can reveal cultural differences across different contexts, for instance with European people (i.e. Italians and Spanish) more sensitive to authorities. Another possible explanation can be offered referring to the specific developmental stage of our sample: the four-factors emerged in our study suggest that social anxiousness in Italian adolescents is reflected on interactions with an unknown other, interactions with authorities, unstructured encounters, and in their sense of inadequacy—scenarios which can be connected to the specific social experiences made in adolescence due to a major openness to the social world (Mohammadi et al. 2020; Wittchen et al. 1999).

4.1 Limitations and further direction of research

Our sample was limited to a specific Italian area, thus it is not representative of diverse locations and limits the generalizability of results across subpopulations. Studies with a more heterogeneous samples are necessary, as well as studies with adolescent clinical samples, in order to replicate the second-order four-components

model or to make comparison studies and determine the most appropriate measurement model.

A new survey could help also to evaluate to remove ξ^I_{IAS1}, or to improve the items of this LOC, since the coefficient is the lowest. Moreover, an extra analysis for the relationship between ξ^I_{IAS2} and ξ^I_{IAS4} could be conducted, since, even if they are is still distinct components, the value in HTMT matrix could be improved, in way to reduce the confidence interval and also the criterion value.

An addition limitation of our study was that we did not include multiple assessment points using the IAS, hindering the measurement invariance of the scale across time. Despite these limitations, this study was the first to evaluate the factor structure and model specifications of the IAS among Italian adolescents using CCA and to offer favorable findings of the higher-order reflective-reflective IAS model.

Declarations

Conflict of interest No potential conflict of interest was reported by the author(s).

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