RESEARCH ARTICLE

Assessing the Heterogeneity of Autism Spectrum Symptoms in a School Population

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The aim of the present study was to assess whether the nature of the main autistic features (i.e., social communication problems and repetitive and restrictive patterns) are better conceptualized as dimensional or categorical in a school population. The study was based on the teacher ratings of two different age groups: 2,585 children between the ages of 10 and 12 (Primary Education; PE) and 2,502 children between the ages of 3 and 5 (Nursery Education; NE) from 60 mainstream schools. The analyses were based on Factor Mixture Analysis, a novel approach that combines dimensional and categorical features and prevents spurious latent classes from appearing. The results provided evidence of the dimensionality of autism spectrum symptoms in a school age population. The distribution of the symptoms was strongly and positively skewed but continuous; and the prevalence of high-risk symptoms for autism spectrum disorders (ASD) and social-pragmatic communication disorder (SCD) was 7.55% of NE children and 8.74% in PE. A categorical separation between SCD and ASD was not supported by our sample. In view of the results, it is necessary to establish clear cut points for detecting and diagnosing autism and to develop specific and reliable tools capable of assessing symptom severity and functional consequences in children with ASD. ***Autism Res** 2018, 11: 979–988*. © 2018 International Society for Autism Research, Wiley Periodicals, Inc.

Lay Summary: The results of the present study suggest that the distribution of autism spectrum symptoms are continuous and dimensional among school-aged children and thus support the need to establish clear cut-off points for detecting and diagnosing autism. In our sample, the prevalence of high-risk symptoms for autism spectrum disorders and social-pragmatic communication disorder was around 8%.

Keywords: autism spectrum disorders; factor mixture analysis; symptom profiles; general child population

Introduction

Dimensional approaches to child psychopathology describe disorders as a continuum of graded symptom severity. According to this continuum, autism spectrum disorders (ASD) are considered the extreme end of a continuous distribution of social communication difficulties and repetitive or restrictive patterns of behavior in the general population [Constantino & Todd, 2003; Spiker, Lotspeich, Dimiceli, Myers, & Risch, 2002; Ring, Woodbury-Smith, Watson, Wheelwright, & Baron-Cohen, 2008; Waterhouse et al., 1996]. Nonetheless, as stated by Frazier et al. [2010], the observed continuity of symptoms does not contradict the discrete categorical distinction found between clinical ASD and typical social communication and restrictive behaviors. In fact, evidence regarding DSM-5 algorithm is supported by a hybrid model that includes both a category (ASD vs. non-ASD) and two symptom dimensions involving nuclear manifestations of ASD [Frazier et al., 2012].

The prevalence of the ASD has been described at around 0.8–1.5% among preschool and school-aged children [Christensen et al., 2016; Nygren et al., 2012; Saemundsen, Magnusson, Georgsdóttir, Egilsson, & Rafnsson, 2013; Sun et al., 2015]. Nevertheless, a larger number of children may exhibit symptoms on the spectrum or be part of the extended or broader autism phenotype. In this regard, several studies based on community samples have revealed a prevalence of high-risk symptoms for ASD between 1% and 5.7% [Nygren et al., 2012; Morales, Domènech-Llaberia, Jané, & Canals, 2013; Möricke, Lappenschaar, Swinkels, Rommelse, & Buitelaar, 2013; Posserud, Lundervold, & Gillberg, 2006; Sun et al., 2015]. In clinical and research settings, individual assessments often reflect subthreshold autistic impairments in children with problems in

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social engagement, as well as in children with other neuro-developmental diagnoses. These children frequently present a high number of symptoms that hinder their social and school adaptation, which makes it difficult for clinicians to delimit the presence of ASD or subthreshold ASD. It is therefore important that the distribution of autism symptoms in the population is further studied in order to delimit and distinguish clinical ASD phenotypes from normative or subthreshold autistic symptoms.

Most of the evidence supporting the idea of a continuous spectrum in autism came from twin and family studies [Constantino & Todd, 2003; Hoekstra, Bartels, Verweij, & Boomsma, 2007; Ruzich et al., 2015; Spiker et al., 2002]. Fewer studies have investigated the variation of autism spectrum symptoms in a wider nonclinical population. In adults, a study based on cluster analysis supported the idea that individual differences were based on the overall magnitude of autism traits [Ring et al., 2008]. In contrast, other studies based on the same methodology reported qualitative differences in adult populations, suggesting that distinct symptom profiles could be found depending on the presence, absence and combination of social and nonsocial (i.e., repetitive or restrictive patterns) features of ASD [Kitazoe, Fujita, Izumoto, Terada, & Hatakenaka, 2016; Palmer, Paton, Enticott, & Hohwy, 2015; James, Dubey, Smith, Ropar, & Tunney, 2016]. In this regard, Palmer et al. [2015] suggested two different profiles that differ inversely in terms of the magnitude of these two features, and Kitazoe et al. [2016] showed the presence of six profiles based on score combinations.

As far as children are concerned, population studies in relation to ASD are even more scarce. Evidence obtained from a clinical population has suggested a categorical distinction between children with ASD and those who display typical behavior within autism-affected families [Frazier et al., 2010], a notable heterogeneity in the phenotypic presentation of the disorder and the presence of several classes based on the severity of social communication impairments, restrictive and repetitive behaviors and adaptive functioning [Georgiades et al., 2013]. In the general population, Möricke et al. [2013] performed a latent class analysis (LCA) and found five different behavioral and developmental profiles in infants aged 14–15 months. Although ASD symptoms were not the exclusive objective of the study, three of the profiles were associated with increased behavioral and developmental problems, including 5.7% of individuals having communication and social interaction problems. The continuous distribution of ASD symptoms suggested by Constantino and Todd [2003] was not confirmed by the LCA conducted by Beuker et al. [2013], who showed the presence of four different profiles in 18-month-old infants: (a) a group without autistic traits, (b) a subclinical group showing social communication problems, (c) a subclinical group showing stereotyped and rigid patterns of behavior, and (d) a group showing high scores in both domains. In contrast, Posserud, et al., [2006] and Kamio et al. [2013] provided evidence of the continuous nature of autistic symptoms in 6- to 15-year-old children, which may be supported by neuroanatomical differences in cortical morphology [Blanken et al., 2015], such as a widespread decrease in cortical gyrification with increasing autistic traits.

Methodologically, most previous questionnaire-based studies on the dimensional versus categorical nature of autistic traits in children have either (a) assessed score distribution at test level [Kamio et al., 2013, Posserud et al., 2006] (b) carried out conventional LCA [Beuker et al., 2013] or (c) used taxometric approaches [Frazier et al., 2010]. All three approaches can provide valuable information, but also have limitations. With regards to the test-scores approach, unimodal and smooth distributions without definite clusters that depart from the bulk of the data, such as those obtained by Kamio et al. [2013] and Posserud et al. [2006], provide evidence that supports the continuous, homogeneous nature of the autistic symptoms. However, the distribution of the test scores is not the same as the distribution of the latent traits that these scores aim to measure [e.g., Mislevy, 1984] and so the evidence obtained is far from being conclusive. With regards to conventional LCA, the main problem is the strong assumption that the measurement variables are uncorrelated within each class [i.e., within-class local independence, e.g., McCutcheon, 1987]. This problem is particularly relevant if previous factor analytic (FA) studies based on these measures suggest a clear and strong factorial structure for the entire group. In this case, the dimensional hypothesis, which implies a single latent class, is untenable from the outset, because it means that the measurement variables are uncorrelated in the general group. Finally, taxometric methods aim mainly to test whether individuals are better described in categorical or continuous terms and are clearly appropriate for identifying simple typologies such as presence or absence of a disorder. However, they assume linear relations (because they are based on covariances) and are limited to two subgroups or classes [e.g., Lubke & Miller, 2015].

The methodology used in this article, factor mixture analysis (FMA), goes far beyond the approaches discussed above in several aspects. First, FMAs are not limited to two classes, and can be used with both continuous and ordered-categorical indicators. Second, they assume a parametric structure within each class and allow a series of structural hypothesis to be tested. Therefore, they allow complex phenotypic structures that are simultaneously categorical and dimensional to be tested [Clark et al. 2013; Frazier et al., 2010; Georgiades et al., 2013, Lubke & Miller, 2015]. As discussed below in more detail, the present research (a) does not limit a priori the potential number of classes to two, (b) uses indicators that are better modelled as ordered-categorical than continuous, and (c) is based on previous FA evidence that suggests a clear dimensional structure in the entire group. For these reasons, FMA is considered to be the most appropriate methodology here.

The aim of the present study was to assess whether the nature of the two main autistic features in children (i.e., social communication problems and repetitive and restrictive patterns) reported by teachers are better conceptualized as dimensional or categorical in a school population. Our starting hypothesis is dimensional, so we expect to find supporting evidence for two continuous gradients related to SCD and ASD symptom severity: one going from the lowest to highest levels of impairment in social communication difficulties without repetitive or restrictive patterns of behavior and another involving impairments in social communication together with repetitive or restrictive patterns.

Method

Study Design

This study was part of the Neurodevelopmental Disorders Epidemiological Research Project (EPINED), a double-phase cross sectional study mainly aimed to determine the prevalence of ASD and social-pragmatic communication disorder (SCD) in Tarragona, Spain. The study was approved by the Ethics Committee at the Sant Joan University Hospital in Reus (13-10-31/10proj5) and supported by the Spanish Ministry of Education and the Catalan Department of Education.

Participants

The total sample consisted of 5,087 children, which represents 97.6% of the potential sample. The participants were from 60 mainstream schools randomly selected from counties in the province of Tarragona, Spain. Of these, 80% were from public schools and 20% from semi-private schools. The study was based on the teacher ratings of two different age groups: 2,585 children between the ages of 10 and 12 (Primary education; PE) and 2,502 children between the ages of 3 and 5 (Nursery education; NE). Table 1 summarizes the sample characteristics.

Procedure

This study was part of a larger study involving both teachers and families. The participation of the families was low (49.4%), but an agreement with the Catalan Department of Education allowed us to collect anonymous data from teachers about the children of nonparticipating families so that we had data on almost the entire sample.

Table 1. Demographic and Psychological Sample Characteristics

	Nursery education	Primary education
Participants, *n* (%)	2502 (97.32)	2585 (97.81)
Age, years, *m* (SD)	4.80 (.50)	10.79 (.56)
Gender, male, *n* (%)	1296 (51.80)	1310 (50.67)
Ethnicity, autochthonous, *n* (%)	1985 (79.34)	2203 (85.22)
Socioeconomic level, *n* (%)		
High	707 (28.27)	613 (23.70)
Medium	1491 (59.59)	1555 (60.15)
Low	304 (12.14)	417 (16.15)

In the first phase of the study, the teachers answered the EDUTEA and provided general socio-demographic data. The teachers had to have known the children for at least three months; if they had not, the questionnaire was answered by the previous year's teacher.

The EDUTEA [Morales-Hidalgo, Hernández-Martínez, & Canals, 2017] is an 11-item questionnaire for teachers that aims to determine children's current behaviors and levels of communication and social interaction. Items are based on DSM-5 criteria; the first seven items gather information relating to ASD criteria and the remaining four relate to SCD [American Psychiatric Association, 2013]. The item format is 4-point Likert (0 = "never or almost never," 1 = "sometimes," 2 = "often," and 3 = "always or almost always"). In usual clinical applications, an overall raw score based on the simple sum of the item scores is used. It has a single cut-off score of 10 (Pc 91.5), which showed good values of sensitivity (87.0%), specificity (91.2%), positive predictive value (.87) and negative value (.99) for ASD and SCD diagnosis. The EDUTEA can be found at the following link https://psico.fcep.urv.cat/Q4/EduTEA/.

Previous factor FAs carried out by the authors showed that the EDUTEA has a clear bidimensional structure, with two identifiable and substantially correlated factors, which were labelled *social communication impairments* and *restricted behavior patterns*. Reliabilities of the scores derived from these scales were good ($\alpha = .95$ and $\alpha = .93$, respectively). However, the factor results also showed redundancies in two item doublets that had to be modelled by allowing for correlated residuals. In order to avoid unnecessary complexities, one item in each doublet was omitted in the present analyses.

Descriptive and Preliminary Analyses

Descriptive statistics were conducted with IBM SPSS 23 to provide the average score for the different age groups and gender. *t*-tests for independent samples and were performed to compare the scores from boys and girls.

Factor Mixture Analysis

As mentioned above, the present study is based on a questionnaire with a clear and well-defined FA structure; therefore, the most appropriate model for assessing the dimensional versus categorical hypothesis is Factor Mixture Analysis [FMA; e.g., Lubke & Muthén, 2005; Lubke & Miller, 2015]. FMA is a hybrid between LCA and FA modelling in which items are allowed to be correlated within each class. Specifically, FMA assumes that there is a common factor structure that influences the item responses in the whole population, and that this therefore allows for within-class variation. However, it also assumes that groups of individuals who behave differently (i.e., classes) can be identified and are thus modelled by using across-class variations in the structure of the common FA model.

In the present FMA modelling, the common influence that leads to within-class variation may be interpreted as the continua of severity in the common factors of *social communication impairments* and *restricted behavior patterns*. This within-class modeling is modelled as a CFA based on the structure obtained in previous studies. Across-class variation is modelled in principle by using a parsimonious and simple basis solution in which the structural parameters are assumed to be the same for all classes (i.e., measurement invariance) but in which factor means are allowed to vary in each class. Substantively, the measurement invariance restriction means that the same factor structure holds for the whole population, while the variations in means indicates class differences in the severity of the symptoms of *social communication impairments* and *restricted behavior patterns*.

Clark et al. [2013] and Lubke and Neale [2008] noted that the invariance restrictions of the basis model above might be too strong, and so lead to bad model-data fit in some applications. To address this potential problem, and for each number of classes, more flexible models were also assessed in which (a) factor variances and covariances, and (b) factor loadings were allowed to vary across classes.

Results

Descriptive and Preliminary Analyses

Table 2 shows the descriptive statistics for the EDUTEA scores by age and gender. Mean scores were significantly higher for boys than for girls in both factors and the total sample scores in nursery and primary education ($P \leq .001$). Children from NE scored significantly lower than PE in both factors and total score ($P \leq .001$).

Table 2. EDUTEA Mean Scores by Age and Gender

	Nursery Education Mean (SD)	Primary Education Mean (SD)	Total sample Mean (SD)
Social communication impairments			
Total	1.91 (3.45)	2.13 (3.65)	2.02 (3.55)
Boys	2.29 (3.80)	2.66 (4.08)	2.48 (3.95)
Girls	1.53 (3.02)	1.61 (3.08)	1.57 (3.05)
Restricted behavior patterns			
Total	.50 (1.36)	.59 (1.47)	.54 (1.42)
Boys	.65 (1.60)	.83 (1.81)	.74 (1.71)
Girls	.34 (1.05)	.35 (.96)	.34 (1.00)
Total score			
Total	2.41 (4.50)	2.72 (4.79)	2.56 (4.66)
Boys	2.94 (5.08)	3.49 (5.55)	3.22 (5.32)
Girls	1.86 (3.76)	1.96 (3.78)	1.91 (3.77)

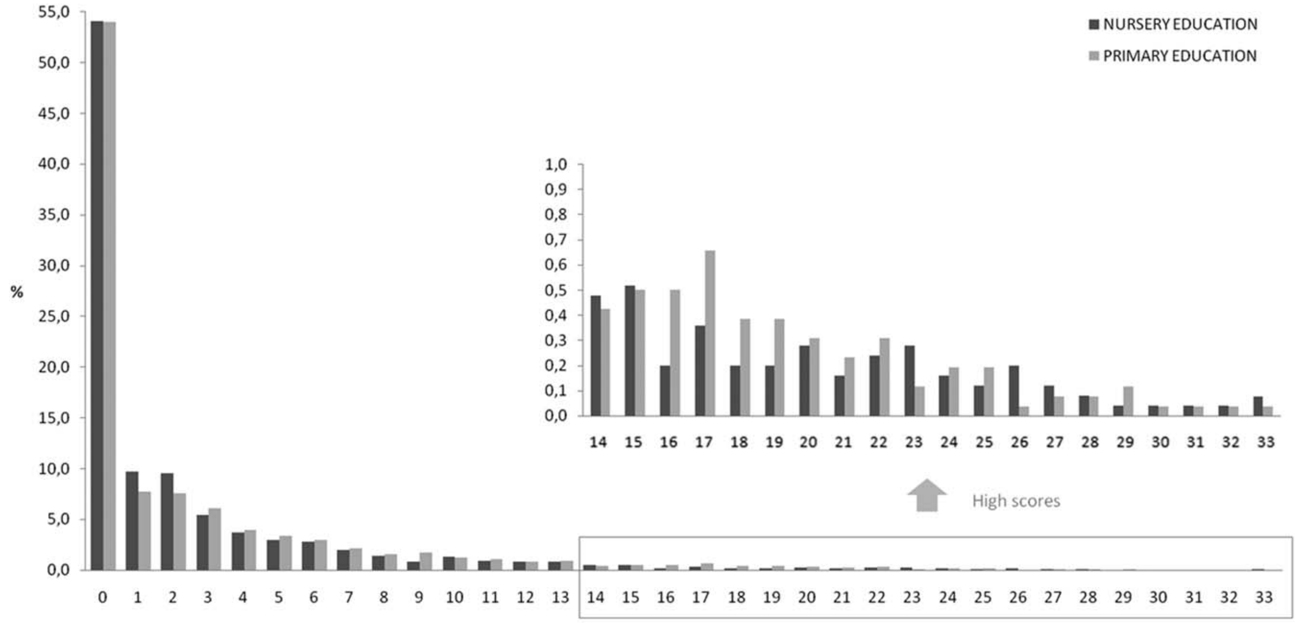
Minimum and maximum scores: total score (0–33), social communication impairments (0–21) and restrictive behavior patterns (0–12).

As far as total score distribution is concerned, the EDUTEA showed a continuous distribution from the lowest to the highest scores (Fig. 1). As expected in a nonclinical population, however, the distribution was strongly and positively skewed, and half of the sample obtained the minimum score in the questionnaire. Teachers found slightly more PE than NE children scoring above the 10-cut-off score ($P = .047$); specifically, this was 7.55% of children in NE and 8.74% in PE, of whom the majority were males (NE: 64.55% and PE: 69.91%).

Mixture Analyses

As suggested by the distribution in Figure 1, most of the item distributions were strongly skewed, with most of the data piled-up in the lowest response categories. This result suggests that treating these scores as continuous variables can lead to biased parameter estimates and an incorrect assessment of model-data fit [Ferrando & Lorenzo-Seva, 2013]. Therefore the most appropriate FMA modelling in this case is that based on categorical variables [Muthén & Asparouhov, 2006]. This modelling is feasible at present but still challenging, and so far it seems to have only been used with binary variables in applications [Lubke & Neale, 2008; Muthén & Asparouhov, 2006].

A sequence of FMA models was fitted to the data by using robust maximum likelihood estimation (MLR) as implemented in the Mplus version 5.1 program [Muthén & Muthén, 2007]. The baseline model was the two-factor model described above, which assumes two dimensional continua, *social communication impairments* and *restricted behavior patterns* that hold for the entire population. In FMA terms, this model is the single-class



Score	NE		PE		Score	NE		PE	
	N	% Cum	N	% Cum		N	% Cum	N	% Cum
0	1354	52.7	1395	54.0	18	5	98.0	10	97.8
1	243	63.8	200	61.7	19	5	98.2	10	98.2
2	239	73.4	196	69.3	20	7	98.5	8	98.5
3	135	78.8	157	75.4	21	4	98.7	6	98.8
4	92	82.5	103	79.3	22	6	98.9	8	99.1
5	74	85.4	88	82.7	23	7	99.2	3	99.2
6	70	88.2	77	85.7	24	4	99.4	5	99.4
7	50	90.2	56	87.9	25	3	99.5	5	99.6
8	36	91.6	41	89.5	26	5	99.7	1	99.6
9	20	92.4	46	91.3	27	3	99.8	2	99.7
10	33	93.8	32	92.5	28	2	99.9	2	99.8
11	22	94.6	29	93.6	29	0	99.9	3	99.9
12	20	95.4	22	94.5	30	0	99.9	1	99.9
13	21	96.3	23	95.4	31	1	99.9	0	99.9
14	12	96.8	11	95.8	32	0	99.9	1	100
15	13	97.3	13	96.3	33	2	100	1	100
16	5	97.5	13	96.8	**Total**	**2502**	**100**	**2585**	**100**
17	9	97.8	17	97.4					

Figure 1. Teacher reported distribution of autism spectrum symptoms in school-aged children.

model and its acceptance would support the hypothesis of dimensionality. Next, two-, three-, and four-class versions of the FMAs described above were fitted, and the fit of the different models was compared. As recommended, especially in complex models such as those considered here, models were estimated with different sets of starting values [Muthén & Asparouhov, 2006]. None of the models reported below showed problems of local minima or convergence. As suggested in Muthén and Asparouhov [2006], conventional LCA was also performed on this data, and goodness-of-fit results were compared to those provided by the FMA. For all 1–4 classes, the fit of the FMA was consistently better than that provided by LCA, which supports the starting hypothesis of this study that FMA provides a superior representation of the data.

Preliminary analyses, both separate and multiple-group, were conducted in order to assess invariance across both educational level (NE and PE) and gender. Results suggested that data can be treated as essentially

Table 3. Fit Indices for the Mixture Categorical Analysis Models of the EDUTEA Factors

k classes	Log-likelihood	AIC	BIC	saBIC	Δ	LMR test (p)	Comments
1	−17864.6	35803.3	36045.0	35927.5	NA		Rmsea= 0.047; CFI= 0.994
2M1	−17854.3	35788.6	36049.9	35922.8	0.91	.99	
2M2	−17848.3	35782.7	36063.4	35927.1	0.46		
2M3	−17770.6	35641.4	35967.9	35809.0	0.44		
3M1	−17851.3	35789.4	36070.4	35933.7	0.57	.55	
3M2	−17842.2	35783.2	36103.2	35947.6	0.43		
3M3	−17733.8	35593.1	36005.4	35805.2	0.37		
4M1	17848.8	35789.7	36090.3	35944.1	0.60	.76	

Note. M1, model with class-specific means, M2, class specific means, variances and covariances, M3 class specific means, variances and covariances, and factor loadings.

The lowest Bayesian information criterion value indicates the most parsimonious and best fitting model. Criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-adjusted BIC (saBIC), Entropy value (Δ), Lo-Mendel-Rubin (LMR) associated probability.

invariant in both cases, and so only the results obtained in the entire sample ($N = 5{,}087$) will be reported from now on.

The selection of the most appropriate number of classes is a complex issue for which there is no still a common accepted methodology. Following Clark et al. [2013] a combination of statistical and substantive model checking procedures was used here. Statistical results are in Table 3.

In principle, the single-class model has quite an acceptable fit by FA standards (see comments in Table 3), and there seem to be no clear improvements when going beyond it. First, the parsimony information criteria (AIC, BIC, and *sa*BIC) do not agree on the "best" model, possibly because the differences obtained across the different solutions are relatively small (the maximum differences in relative terms are about 0.5%). Second, the Lo-Mendel-Rubin probability results obtained from the basis model-1 indicate that models with an increased number of classes should not be chosen over the single-class model. Third, the entropy values clearly decrease when increasing the number of classes and freeing invariance constraints so that only the 2-class basis model-1 reaches an acceptable value. In the remaining solutions, entropy values are unacceptably low, which means that the differentiation of individuals in terms of the class they belong to is far from clear.

At the substantive level, examination of the 2-class basis model-1 solution (the only alternative reliable solution in entropy terms) suggested simply a categorical distinction between children with high raw scores in the questionnaire (14.29%) and children with low scores (85.71%). Children in the first class showed a mean score of 8.70 (s.d. 7.28), which is close to the EDUTEA 10 cut-off score for ASD risk. The mean value in the second class was 1.54 (s.d. 3.02) which indicates a minimum risk. Overall, then the results tend to support the dimensional view of both factors, in which all the children are located in a continuum of symptoms ranging from low or minimum scores for *social communication impairments* and *restricted behavior patterns* to high and maximum scores for both factors.

In order to provide additional evidence regarding the dimensional hypothesis, as suggested in Muthén [2001], the estimated factor scores from the baseline single-class solution were plotted and are shown in Figure 2 (note that the metric of these scores is standard, with zero mean and unit standard deviation). It is clear that the scores are arranged along the principal axis of both factors and that the scatter of points is homogeneous, with no separate clusters or natural cut points that would have suggested the presence of more than one class. The low proportion of individuals in the upper-right corner of Figure 1 are those that scored high for both factors and may thus be considered as children at risk of ASD symptoms.

Discussion

The classic dilemma about the dimensional versus categorical nature of many psychopathological constructs also affects the autistic spectrum. While most of the evidence supporting the idea of a continuous spectrum in autism has come from clinical populations, a few studies have investigated the variation of autism spectrum symptoms in broader nonclinical populations. Nowadays we assume that manifestations of autism are also present to a greater or lesser extent in the general population, but despite the importance of this issue to improving detection and diagnosis procedures, studies about dimensionality are neither extensive nor conclusive in child community populations [Beuker et al., 2013; Blanken et al., 2015; Kamio et al., 2013; Posserud et al., 2006].

As expected in the general population, a high proportion of the sample in the present study (52–54%) did not show any evidence of autistic symptoms. The distribution of the symptoms was strongly and positively skewed but continuous both in nursery and primary

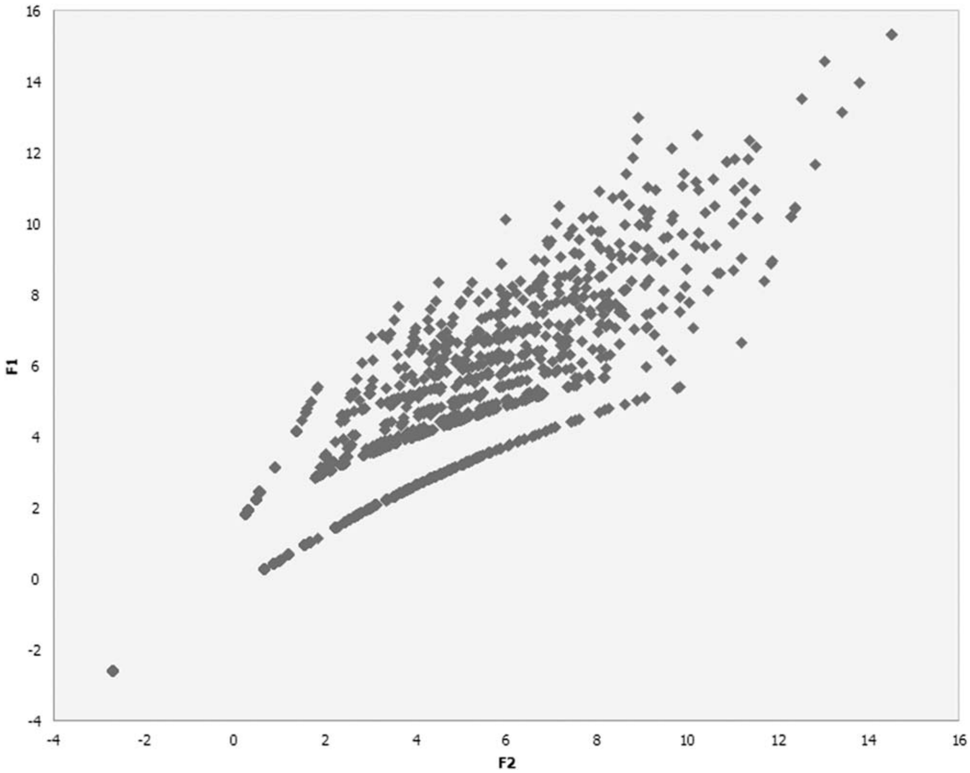


Figure 2. Estimated factor scores from the two-factor EDUTEA solution. F1: Social communication impairments; F2: Restricted behavior patterns.

education, which is congruent with the continuous and homogeneous nature of the autistic symptoms described in previous studies [Constantino & Todd, 2003; Kamio et al., 2013; Posserud et al., 2006]. Therefore, in spite of the extreme distributions that were found, preliminary descriptive results provide some marginal evidence supporting the dimensional hypothesis. A total of 7.55% of NE children and 8.74% in PE showed high scores in EDUTEA, which suggests a risk for SCD or ASD according to DSM-5 criteria. Boys scored significantly higher than girls in social communication impairments and restrictive behavior patterns, as has been reported by other authors [Christensen et al., 2016; Kim et al., 2014; Sun et al., 2015].

The FMA-based results obtained in the present study provided evidence of the dimensionality of autism spectrum symptoms in child population. These results were based on teachers' responses to EDUTEA, which is a two-factor questionnaire that assesses the dyad of impairment described in the ASD definition [Mandy, Charman, & Skuse, 2012; Shuster, Perry, Bebko, & Toplak, 2014]. By means of FMA, a single-class model including a continuous gradient of symptoms in both factors was thought to be the most tenable solution. Overall, results did not support evidence for different classes in terms of symptom profiles, age or sex-specific characteristics. Thus, despite obtaining significant differences in mean scores, the symptom profile remains stable across gender and age, which implies continuity in the presentation of symptoms between the first years of life and school age and also across gender.

Previous studies of child populations have reported different profiles that reflect the presence of other behavioral and developmental problems which are not assessed in our study [Möricke et al., 2013] and which also reflect the presence of the core symptoms of autism, thus supporting a categorical presentation of symptoms [Beuker et al., 2013]. Similar categorical results were found in adults [Kitazoe et al., 2016; Palmer et al., 2015; James et al., 2016]. In clinical samples, Frazier et al. [2010] supported a categorical distinction between children with ASD and those without the diagnosis and Georgiades et al. [2013] identify several classes among children with ASD on the basis of symptom severity and adaptive functioning. While the differences with respect to the present study may be due to the use of different samples, measurement instruments, and the consideration of different types of problems, they may also be partly due to the use of different methodologies. As discussed above, FMA is thought to be the most appropriate approach for the type of data that was analyzed. And, in particular we would like to stress that (a) its use was intended to prevent spurious latent classes from appearing, and (b) the analyses treated the item scores as ordered-categorical outcomes also with the aim of preventing spurious results. Categorical FMA is a challenging methodology that has also been used with binary responses in applied research. Consequently, the present study can be considered to take a novel approach at the applied level.

The solution we propose here must be considered to be tentative, and its possible generalizations must be taken cautiously. Thus, the lack of compelling evidence for class differences might well have been different in clinical samples or when using different measures. Furthermore, even in the conditions considered in the present study, further validity evidence should be collected [e.g., Clark et al., 2013], and this evidence includes replication in different samples as well as empirical relations with both background variables and external criteria.

In psychopathological terms, acceptance of the single-class model as the most appropriate and parsimonious allowed us to assess the variation in severity of social communication symptoms and restrictive or repetitive behavior in the general population and identify two continuous gradients. The results provide us with a better description about the presentation of ASD symptoms in the population and contribute to the field of etiopathogenesis because it has been proven that variability in autism traits among the population could be related to the presence of inherited or de novo genetic risk factors in the general population [Robinson et al., 2016]. However, from a clinical point of view, our data did not support a differentiated picture of SCD manifestations. Although EDUTEA specifically collects manifestations of social pragmatic communication disorders, the analyses did not show the presence of a second class that collects these manifestations separately from those in ASD. Therefore, a categorical separation between SCD and ASD is not supported by our sample, a finding which is in keeping with that of Brukner-Wertman, Laor, and Golan [2016]. One possible explanation for this could be that SCD is probably best conceptualized as a dimensional symptom profile that may be present across a range of neurodevelopmental disorders [Norbury, 2014]. Regarding the questionnaire, the results indicate that EDUTEA assesses the whole dyad of ASD symptoms.

Finding a quantitative or dimensional distribution of symptoms demonstrates the need to establish clear cut-off points for detecting and diagnosing autism. The distinction between clinical and nonclinical diagnosis should consider symptom severity and functional consequences, as required by DSM-5. However, this is not a simple task because practice recommendations for differentiating between levels remain undetermined [Weitlauf, Gotham, Vehorn, & Warren, 2014] and the presence of associated problems and comorbidities also aggravates the severity of psychopathological manifestations [Posserud, Hysing, Helland, Gillberg, & Lundervold, 2016].

The main strength of the study was the sample size and the suitability of the questionnaire and statistical method for assessing the dyad of symptoms described in ASD. However, future research should replicate our study in larger population samples and with wider age ranges. To our knowledge, this is the first study that assesses the heterogeneity of ASD symptoms in a Spanish school population and its results indicate a continuous and dimensional presentation of autism spectrum symptoms in a child population.

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