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A Person-Centered Perspective on Differential Efficacy of Early Behavioral Intervention in Children with Autism: A Latent Profile Analysis

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Abstract

Background: Individuals with autism spectrum disorder (ASD) present heterogeneous symptom manifestations and responses to intervention. Despite being well-established, early intensive behavioral intervention (EIBI) has produced inconsistent responding across studies. Investigating individual differences and identifying more homogenous subgroups in samples may lead to a better understanding of symptom heterogeneity in ASD and response to EIBI.

Method: Adopting a person-centered perspective, we conducted latent profile analyses (LPA) to explore the presence of homogenous subgroups in our sample of 233 preschoolers with ASD receiving early behavioral intervention services. We investigated predictors of group membership using logistic multinomial regressions and outcomes of membership with the BCH approach available in Mplus.

Results: We found four latent profiles in our sample: a mild impairment profile, a severe impairment profile, and two intermediate profiles with combinations of mild to moderate autistic symptoms, adaptive functioning, and intellectual functioning. Only the annual family income predicted profile membership. All profiles made progress during the intervention period, with varying magnitudes of change. During the follow-up period, the moderate impairment and the severe impairment profiles showed stability or improvement in adaptive functioning, while the two mild impairment profiles showed a slight decrease.

Conclusions: Our study contributes to the literature by suggesting the presence of distinct profiles with differences in their response to EIBI. The profiles associated with better short-term outcomes were different than the profiles who maintain their gains more consistently over time. This finding may guide both practitioners and researchers assessing the effects of intervention.

Keywords: autism spectrum disorders, differential response, EIBI, heterogeneity, latent profile analysis, person-centered.

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According to the Diagnostic and Statistical Manual of Mental Disorders – 5th edition (DSM-5), autism spectrum disorder (ASD) is a neurodevelopmental condition that is characterized by persistent deficits in social communication and interaction across various contexts, and by the presence of restricted, repetitive patterns of behaviors and interests (American Psychiatric Association [APA], 2013). In addition, individuals with ASD differ in terms of intellectual functioning (Wiggins et al., 2012), patterns of cognitive strengths and weaknesses (Munson et al., 2008), and levels of adaptive functioning (Ray-Subramanian et al., 2011; Szatmari et al., 2002). On one end of the autism spectrum, individuals have mild difficulties, occasional needs, and function with a low level of support, while on the other end of the spectrum, individuals experience serious difficulties that affect many areas of activities and require significant and ongoing support. Without interventions, manifestations of ASD remain stable across the lifetime of the majority of diagnosed individuals (Bieleninik et al., 2017).

Besides heterogeneity in symptom presentation, individuals with ASD tend to respond differently to intervention (Sherer & Schreibman, 2005). Even though early intensive behavioral intervention (EIBI) is considered one of the most effective interventions for children with ASD (Health Technology Inquiry Service, 2008; INESSS, 2014; Maglione et al., 2012; National Autism Center, 2009; National Institute for Health and Care Excellence, 2013; Prior & Roberts, 2012), some children only make modest, or even no improvement (Reichow et al., 2018). Such variability in response to treatment complicates attempts at predicting clinical outcome, and individualizing treatment targets and strategies (Kim et al., 2016; Masi et al., 2017; Zheng et al., 2020). Heterogeneity in outcomes continues to be poorly understood and the characteristics of children that may influence efficacy of EIBI are still debated (Eapen et al., 2013; Reichow et al., 2018).

Studies examining predictors of EIBI outcomes have produced conflicting results on some individual characteristics, such as age at enrollment (Bieleninik et al., 2017; Makrygianni & Reed, 2010), intellectual functioning (Makrygianni & Reed, 2010; Reed, 2016; Tiura et al., 2017), and autistic symptoms (Flanagan et al., 2012; Reed, 2016). The influence of adaptive functioning is more consensual, and numerous studies support that high adaptive functioning in children is associated with improved efficacy of EIBI (Eldevik et al., 2010; Flanagan et al., 2012; Reed, 2016; Reichow, 2012; Sallows & Graupner, 2005; Vivanti et al., 2014). A possible explanation for the disagreement concerning the potential predictors of efficacy is that combination of variables (i.e., the profiles of the children) may be more important than the individual contribution of these characteristics considered in isolation. Several researchers recommend accounting for individual differences and identifying more homogenous subgroups in samples to better understand symptom heterogeneity in ASD and response to EIBI across children (Eapen et al., 2013; Georgiades et al., 2013; Tiura et al., 2017).

A person-centered perspective could guide the identification of more homogenous subgroups in the population of autistic children. Contrary to the variable-centered approach (the most commonly used in social and psychological sciences) that investigates the relationships between variables, the person-centered approach explores the relationships between individuals and aims to group individuals into subgroups (Bergman & Trost, 2006; Laursen & Hoff, 2006). In the person-centered approach, the associations between the variables may therefore be different depending on the groups of individuals identified within a sample. Adopting a person-centered approach may help inform evaluative research in ASD, as one of its advantages is that the generalization of findings applies to persons and not variables (Magnusson, 1998). Hence, the results of person-centered studies are likely to translate to clinical applicability.

In this context, a crucial question is on what basis should we identify the subgroups when considering the autistic population? Previous studies have adopted two different approaches. Some researchers have attempted to identify subgroups relying solely on autistic symptoms. For example, Wiggins et al. (2012) investigated subgroups based on the Childhood Autism Rating Scale (Schopler et al., 1980), and Georgiades et al. (2013) used the Autism Diagnostic Interview Revised (Rutter et al., 2003). Both studies found three subgroups in their sample of autistic children, with varying severity of social communication deficits, and fixated interests and repetitive behaviors. The purpose of these studies was related to the conceptualisation of the diagnostic criteria for ASD. Some authors have pointed out that focusing only on measures designed to screen for diagnosis of ASD (i.e., distinguish ASD from non-ASD) to identify subgroups is problematic, because such tools were not meant to describe variability within the autistic population (Zheng et al., 2020).

In another study, Harris et al. (2021) conducted two separate latent class analyses based on the two criteria of ASD as defined by the DSM-5 (APA, 2013), namely social communication skills as well as restrictive and repetitive behaviors. The researchers measured autistic symptoms by combining the results from the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2; Lord et al., 2012) and the clinical observations documented by physicians in the medical records of the participants. Their results suggested a three-class model for social communication skills model and a two-class for the restrictive and repetitive behaviors. Looking at the relationship between demographics (i.e., sex, age and annual income) and profiles membership, being younger and a girl were associated with the class that exhibited fewer restrictive and repetitive behaviors. Their analyses found no association for annual income. To our knowledge, this study is the only one to date to explore the relationship between demographics and profiles in toddlers with autism.

More recently, researchers combined multiple features, such as autistic symptoms, cognitive abilities, and adaptive functioning, to investigate the presence of subpopulations in autistic children (Kim et al., 2016; Zheng et al., 2020). Zheng et al. (2020) identified three subgroups in a sample of 188 preschoolers with ASD. Children in the first cluster (51%) displayed relatively high cognitive, language and adaptive abilities, and relatively low levels of social symptoms, repetitive behaviors, and sensory issues. Children in the second cluster (24.5%) presented cognitive, language and adaptive abilities similar to first cluster, but more severe social deficits as well as repetitive and sensory behaviors. Children in the third cluster (24.5%) showed lower cognitive, language and adaptive abilities, and more severe social, repetitive, and sensory symptoms.

In another study, Kim et al., (2016) found four clusters among 95 toddlers with ASD. The first cluster (36%) constituted the highest functioning group and was characterized by moderate impairments in social communication and repetitive behaviors. The second cluster (16%) grouped relatively high-functioning children that had similar cognitive skills, but less severe social affective symptoms and lower adaptive functioning than the first cluster. The third cluster (31%) constituted a relatively low-functioning group, with severe autistic symptoms and some delays in adaptive skills, but better verbal and nonverbal skills then the fourth cluster. The fourth cluster (17%) represented the very low-functioning group and was characterized by severe autistic symptoms, and significant delays in all areas of functioning. The study conducted by Kim et al. (2016) is particularly relevant because it explored the relationships between the identified subgroups and diagnosis stability, clinical presentation, and intervention outcomes. Children in the sample received various type of intervention, including applied behavior analysis, Floor

Time, speech therapy, and occupational therapy. To our knowledge, no study has directly verified the relation between membership to a subgroup and EIBI outcomes.

Expanding on the findings of a previous study which evaluated the effectiveness of EBI[1] using a variable-centered approach (Préfontaine et al., 2021), the purpose of the current study was to (1) use a person-centered approach to identify distinct profiles of children receiving EBI based on measures of autistic symptoms, three domains of adaptive functioning and three subscales of IQ, (2) examine whether sociodemographic characteristics predicted profile membership, and (3) assess whether profile membership was associated with different response to EBI. Together, these questions sought to better understand the differential efficacy of EBI in children diagnosed with ASD.

Method

Participants and Procedure

The Joint Research Ethics Board for Public Rehabilitation Centers for Persons with Intellectual Disabilities and ASD in Quebec approved the research project. Parents had to provide written consent for their children to participate in the study. The sample comes from a larger research project (see Rivard et al., 2014; 2019) and consisted of 233 children (79% boys) diagnosed with ASD aged between 2.50 to 5.75 years old (M = 4.34, SD= 0.47) who received one year of low-intensity intervention (between 4 and 12 hours weekly, 53.9% of participants) or moderate-intensity intervention (between 16 and 20 hours weekly, 46.1% of participants). The center determined the intervention intensity for each child by assessing their needs at enrollment, and considering the preferences and availability of the parents. Regardless of the intensity option,

[1] Given that the intensity offered to the participants may not qualify the intervention as being "intensive", we will use the expression early behavioral intervention (EBI) to refer to their program to prevent misleading the reader. The only difference between EIBI and EBI is the number of weekly hours of intervention.

the intervention was based on applied behavior analysis and qualified for early behavioral intervention. There were no statistically significant differences between the two intensity groups regarding their characteristics and the effect of intervention, as investigated in a previous study (Préfontaine et al., 2021). Children who participated in the study had to meet the following inclusion criteria: (a) have a diagnosis of ASD provided by a pediatric psychiatrist and independently confirmed by a multidisciplinary team, (2) be aged 5 years old or younger, and (3) live within the geographical area served by the rehabilitation center located in a suburban and rural region near Montreal, Quebec, Canada.

The larger research project used a prospective longitudinal design with three annual assessments, where time 1 represents baseline (n = 233), time 2 represents post-intervention (12 months after baseline; n = 219) and time 3 represents 12-months follow-up after the end of the intervention (n = 64). Since most of the sample had entered preschool at time 3 and were no longer receiving services from the readaptation center, they may have been harder to reach for the completion of the 12-months follow-up. This challenge may explain high attrition at time 3. Attrition analyses conducted in a previous study (Prefontaine et al., 2021) suggested that the data were missing at random. To explore the presence of distinct profiles on the children, the current study used the data from time 1.

Measures

Demographics

Parents of participants completed a sociodemographic questionnaire, and their responses were then coded in the database. Gender of the participants was a dichotomous variable (code 1 = female and 2 = male). Age was a continuous variable, where decimals allowed to record the exact age of the participants (i.e., 2-year-old and 6-month-old is coded 2.5). Annual family income was an ordered-categorical variable (code 1 = $10,000 to $29,999, 2 = $30,000 to $49,999, 3 =

$50,000 to $69,999, 4 = $70,000 to $89,999, and 5 = Over $90,000) and were reported in Canadian dollars.

Autistic Symptoms

A parent and a special education technician[2] completed the *Childhood Autism Rating Scale – Second Edition* (CARS-2; Scholper et Van Bourgondien, 2010) to measure autistic symptoms. The CARS-2 contains 15 items assessing different apparent difficulties in children with ASD on a 4-point scale from one to four (1 = normal, 4 = severely abnormal). Higher scores indicate more severe autistic symptoms (< 30 indicate minimal or no symptoms, 30 to 36.5 indicate mild to moderate symptoms, 37 to 60 indicate severe symptoms). We used the average score between the two respondents because they were highly correlated (r = .67 to .81 depending on time point).

Adaptive Functioning

Using the parent/primary caregiver form for young children (0 to 5 years old), a parent completed the *Adaptive Behavior Assessment System-II* (ABAS-II; Harrison and Oakland, 2003) to measure adaptive functioning. This form of the ABAS-II contains 241 items rating the performance of various adaptive behaviors on a 4-point scale, from zero to three (0 = never, the child is unable, 3 = always when necessary). The results provide a general adaptive composite score and a score for each of the three domains of adaptive functioning, namely the conceptual, social, and practical domains. In the present study, we used the scores of the three adaptive domains.

Intellectual Functioning

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[2] Special education technicians is a terminology unique to the province of Quebec and refers to college-level technicians.

Research assistants supervised by a psychologist administered the *Wechsler Preschool and Primary Scale of Intelligence* (WPPSI-III; Wechsler, 2003) to measure intellectual functioning. The WPPSI-III totalizes 15 sub-tests capturing five dimensions (i.e., verbal comprehension, visuospatial performance, fluid reasoning, working memory and information processing speed). In addition to the full-scale IQ, results provide three subscale scores, namely verbal IQ, performance IQ and general language composite. In the present study, we considered the standard scores for verbal IQ, performance IQ and general language composite because they provide more specific information on cognitive abilities than the full-scale IQ.

Response to EBI

In a previous study adopting a variable-centered approach (Préfontaine et al., 2021), we conducted latent growth curves (LGC) analyses to capture changes in autistic symptoms and adaptive functioning (general adaptive functioning and the conceptual, social, and practical domains of adaptive functioning) of children receiving EBI in a community setting. The results showed a linear decrease in autistic symptoms from baseline to follow-up (T1 to T3), and nonlinear changes in adaptive functioning characterized by improvement during the intervention period (T1 to T2), followed by stability in adaptive functioning during the follow-up period (T2 to T3). To better understand the impact of profile membership on response to EBI, the estimates of individual trajectories (i.e., factors scores) from these LGC analyses were saved and used as the outcome variable, response to EBI, in the current study. For autistic symptoms, response to EBI refers to slope 1, that estimates the expected change between each time point from T1 to T3, as the change detected was linear across the entire study. For the three domains of adaptive functioning, response to EBI refers to two slopes because the LGC analyses detected nonlinear changes. Slope 1 is the estimated expected change during the intervention period (T1 to T2) while slope 2 is the estimated expected change during the follow-up period (T2 to T3). Because LGC estimates a model, the analyses produced factor scores of growth parameters (i.e., slope 1 and slope 2) for the entire sample (n = 233), not only for the cases for which we had complete data. Using the individual estimates (or factor scores) of LGC instead of the scores at T3 allowed us to examine association between the profile membership and the change (i.e., progress) made by the children receiving EBI.

Analytical Strategy

First, we performed descriptive statistics using SPSS Statistic for Windows, version 26.0 and then used Mplus 8.3 (Muthén & Muthén, 2017) to conduct Latent Profile Analyses (LPA; Muthén & Muthén, 2000) with the maximum likelihood estimation robust (MLR; Shi et al., 2021), which corrects the standard errors for non-normality in the data. Missing data were handled using full-information maximum likelihood estimation, which allow to use every case in the sample (Enders, 2010). We used autistics symptoms, the three domains of adaptive functioning (conceptual, social, and practical domains) and the three subscales of IQ (verbal IQ, performance IQ, and global language composite) as mixture indicators (i.e., the variables used to identify or differentiate the profiles). We followed the recommendations of Masyn (2013) to test four different parametrizations of the means and variance-covariance matrix: (1) conditional independence with equal variance across profiles model (i.e., Mplus defaults), (2) conditional independence with unequal variance across profiles model, (3) conditional dependence with variance and covariance equal across profile, and (4) conditional dependence with unequal variance and covariance across profiles. For each parametrization, the analyses involved iteratively specifying the LPA models, starting with one profile up to six profiles. In order to avoid convergence to a local solution (i.e., false maximum likelihood; Hipp & Bauer, 2006), we estimated the models with 5000 random sets of starts values, with the 50 best retrained for the final optimization.

A critical question when conducting LPA is determining the number of profiles in the data. Various statistical tests and indices can support decision-making (Masyn, 2013; McLachlan & Peel, 2000). As log likelihood in mixture models are not distributed according to the chi-square distribution, the regular likelihood ratio test cannot be used to compare models. The Vuong, Lo, Mendell and Rubin’s test (VLMR) and the Bootstrap likelihood ratio test (BLRT) are adjusted likelihood ratio tests that allow for the comparison of the current model to a model with k-1 profiles. A nonsignificant VLRM or BLRT indicates that the more parsimonious model is better fitting (Ferguson et al., 2019). Information criteria can also be used to determine the best model in the data. The Akaike information criterion (AIC), Consistent AIC (CAIC), Bayesian information criterion (BIC) and the sample-size adjusted Bayesian information criterion (SABIC) are such indices that allow comparing model with different number of classes, with lower values indicating a better fit. The magnitude of the differences between models is also important for interpretation, because in some samples, AIC, CAIC, BIC and SABIC values tend to continuously decrease as the number of profiles increase (Ferguson et al., 2020; Masyn, 2013). Consequently, making an elbow graph reporting these values for each model can support interpretation.

In LPA, entropy estimates the degrees of classification uncertainty (or precision with which individuals are classified) for each profile (Ferguson et al., 2019). Lower values of the entropy statistic indicate more uncertainty and values greater than 0.80 indicate that the profile classification is adequate (Tein et al., 2013). Entropy should not be used for profile enumeration, but it can support the comparison of models. Finally, given our use of a small sample, the number of individuals in the smallest class should also be taken into account as it could influence replicability of the model (Ferguson et al., 2020; Muthén & Muthén, 2000). Beyond the statistic tests and indices, the retained model should be meaningful conceptually (Ferguson et al., 2020; Morin & Litalien, 2019)

Once the final unconditional model was determined, we examined whether a number of variables would predict group membership (i.e., covariates having an impact on profile membership) and we evaluated group differences on outcomes (i.e., adjusted mean differences on outcomes between latent class). Examining if external correlates (i.e., different from the mixture indicators) can predict group membership or outcomes is one important aspect to demonstrate the external validity of a classification (see Skinner, 1981). Our analyses directly incorporated predictors to the final model to predict class membership through a multinomial logistic regression (Morin & Litalien, 2019)**.** For the outcome, we opted for the BCH approach available in Mplus, which has the advantage of avoiding shifts in the profiles from the unconditional model (Asparouhov & Muthén, 2014; Bakk & Vermunt, 2016).

Results

Descriptive Analysis

Table 1 reports descriptive statistics of the sample. The sample included children with varying characteristics, as shown by the large variances**.**

Latent Profile Analysis

Table 2 reports the fit indices of the LPA models; the upper panel shows results for conditional independence with equal variance across profiles, while the lower panel displays results for conditional independence with unequal variance across profiles. Models with the two other parametrizations led to convergence problems. Looking at the information criteria, AIC, CAIC, BIC and SABIC were constantly lower in the conditional independence with unequal variance models than in the conditional independence with equal variance models when considering the same number of profiles. Therefore, we retained conditional independence with unequal variance across profiles as the optimal parametrization.

As the information criteria continuously decreased as the number of profiles increased, we looked at the elbow graph (see Figure 1) to inform the selection of the best model. Visual inspection suggested that the optimal solution was between three and four profiles. To help with the final model selection, we created histograms with the characteristics of the latent profiles to see how profiles were distinct from one another and verify conceptual relevance. Considering all information, we opted for the four profiles model, as this solution had good entropy, reasonable number of children in the smallest class and each profile was qualitatively different from each other. We did not retain the solution with five profiles, because two profiles seemed to result from a quantitative division of the same profile, rather than being qualitatively different from each other. Table 3 presents the estimated posterior probabilities for the final latent profile model. Values were excellent and suggest high precision in the classification of children between the different profiles.

Table 4 presents the latent profile means and variances on the mixture indicators. Figure 2 depicts these characteristics in *z* scores comparing the value of each profile to our entire sample; hence, zero represents the mean of our sample whereas each profile z-score shows the deviation from this sample mean. Note these z scores were not used to conduct the LPA analyses and were only realised to facilitate the interpretation of the histogram. Children in the first latent profile had low autistic symptoms combined with the highest adaptive and intellectual functioning. This *mild impairment with average IQ profile* described 27.47% of the children (n = 64). Children in the second latent profile had the lowest autistic symptoms, similar adaptive functioning than the mild impairment with average IQ profile, but had lower average IQ. This *mild impairment with lower average IQ* profile also described 27.47% of the children (n = 64). Children in the third latent profile had moderate autistic symptoms, and low intellectual and adaptive functioning. This *moderate impairment profile* described 24.46% of the children (*n* = 57). Finally, children in the fourth latent profile had the most severe autistics symptoms combined with the poorer intellectual and adaptive functioning. This *severe impairment profile* described 20.60% (n = 48) of the children in our sample.

Predictors of Profile Membership

Table 5 reports the multinomial logistic regression of the various predictors of group membership, using the "mild impairment with average IQ profile" as the reference group. Lower annual income predicted membership to the moderate impairment profile and the severe impairment profile. This result suggests that children living in families with lower annual income were more likely to be in the moderate impairment and severe impairment profiles than in the mild impairment profile with average IQ. Younger age marginally predicted membership to the severe impairment profile. Gender does not influence membership to the different profiles.

Profile Responses to EBI

Table 6 reports the distinctions between profiles' response to EBI, and Figure 3 depicts the estimated trajectories of each profile for all outcomes across the three time points. All profiles showed a small reduction in autistic symptoms from baseline to follow-up, with the biggest improvement made by the children in the mild impairment with lower average IQ. As stated in the measures section, results of the effectiveness study from which the outcome variables come from showed a linear decrease in autistic symptoms from baseline to follow-up. Thus, response to EBI pertaining to autistic symptoms constituted only one outcome variable. Regarding the three domains of adaptive functioning, results revealed that the different profiles responded differentially to the intervention. During the intervention period (slope 1), all profiles made progress on the three adaptive domains, with the greatest improvement made by children in the mild impairment with average IQ and mild impairment with lower average IQ profiles for all outcomes. Looking at the follow-up period (slope 2), profiles were quite different in the way they evolved. For the conceptual and social domains of adaptive functioning, the moderate impairment and severe impairment profiles continued to progress, while the mild impairment with average IQ and mild impairment with lower average IQ profiles showed a small decrease. For the practical domain, the mild impairment with average IQ profile continued to slightly improve, while the mild impairment with lower average IQ, the moderate impairment and the severe impairment profiles stayed relatively stable.

Discussion

Our study contributes to the literature on the heterogeneity of symptom presentation and response to intervention in ASD. Similar to Kim et al. (2016), we identified four profiles, including a mild impairment profile, a severe impairment profile, and two intermediate profiles with combinations of mild to moderate alterations for autistic symptoms, adaptive functioning and intellectual functioning. Even though we labeled profiles by qualifying the severity of impairment, it should be noted that even in the mild impairment with average IQ and mild impairment with lower average IQ profiles, children were far under the level of adaptive functioning of their typically developing peers. Only children in the mild impairment with average IQ profile had IQs in the normal range. Within a given profile, the three domains of adaptive functioning are relatively homogeneous, as are the three subscales of IQ. Concerning the potential predictors of profile membership, only lower annual income predicted membership to the moderate and severe impairment profiles, which underlines the possibility that these family had less resources and support to alleviate (or intervene on) the symptoms before receiving formal support from public agencies. Gender did not influence profile membership in our sample, which was unexpected considering previous studies had shown behavioral and cognitive differences across genders (Frazier et al., 2014; Hull et al., 2017). As our sample was considerably younger, this disparity may be the result of the specific age group studied (Zheng et al., 2020).

Profiles showed distinction in their response to EBI. During the intervention period, the mild impairment with average IQ and mild impairment with lower average IQ profiles achieved the largest gains on all outcome variables, which is consistent with the findings from Kim et al. (2016). Despite the magnitude of the change being smaller, the moderate impairment and severe impairment profiles also improved on all outcome variables. At the follow-up period, the severe impairment and moderate impairment continued to improve or maintained their gains in the conceptual and social domains, while the two mild impairment profiles showed small reductions. These results suggests that although their progress is smaller and slower, the improvements are sustainable over time for children who present more impairment when they enter services. Hence, evaluative studies should consider long-term effects when assessing intervention. As children were no longer receiving services from the readaptation center and had started school during the follow-up period, we have no information on the type of support each child received in class at school. One hypothesis is that the children with mild impairments received less support from their school than the children in the moderate impairment and severe impairment profiles. This observation highlights the need to conduct more research on the factors that influence maintenance of improvements after receiving EBI. In addition, these results show that the person-centered perspective may help uncover differential patterns of change that would remain unknown in a variable-centered perspective.

Our study has some limitations that should be discussed. Given that we had a limited number of variables, the external validators (i.e., outcome variables used for the external validation of the profiles) were changes on the initial level of some of the variables used to identify the profiles (i.e., mixture indicators). This method is unconventional, but it allowed us to identify profiles of children from their pre-intervention characteristics, and to associate them with their response to EBI during the intervention and follow-up periods. Thus, results of cross-sectional profiles at time 1 may support practitioners in predicting who will benefit most from EBI and allow them to adapt their recommendations prior to beginning treatment. To expand these findings, future research should use latent transition analysis, which identify profiles at different time points and investigate the probability of a transition from a profile to another across time (Muthén & Muthén, 2000). An additional possibility involves using latent growth mixture modeling (Morin & Litalien, 2019), but these analyses typically require large samples. Another limitation concerns the response to EBI variables, which were computed from an effectiveness assessment that used a correlational design. The absence of control group limits the causal inferences between the intervention and the observed changes, and does not control for maturation effects. In addition, results regarding the association between profile membership and the follow-up period (T2 to T3) must be interpreted with caution, given the high attrition in our sample between these time points. Future research should attempt to limit attrition by using retention strategies. It should be noted that, because the profiles we made from cross-sectional data at T1, this limit does not jeopardize the result of the LPA analysis.

Implications

Our study is one of the few to explore the presence of subgroups in preschoolers with ASD, and to investigate predictors and outcomes of membership. To our knowledge, our results are the first to show that the profiles associated with better short-term outcomes of EBI are different than the profiles who maintain their gains better. This finding could guide both practitioners and researchers assessing the effects of EBI. Future research should try to replicate those findings with a larger sample and consider using designs with more time points during the follow-up to better understand the factors associated with the maintenance of outcomes.

CRediT authorship contribution statement

Isabelle Préfontaine: Conceptualization, Methodology, Formal analysis, Writing – Original Draft. **Julien Morizot:** Supervision of analysis, Writing – Review and editing. **Marc J. Lanovaz:** Supervision, Writing – Review and editing. **Mélina Rivard:** Methodology, Data Curation, Review.

Declaration of Competing Interest

The authors of this paper declare no conflicts of interest in the completion of the study or the preparation of this manuscript. Authors have no relevant financial relationships to disclose.

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Table 1

Descriptive Statistics of the Sample

Variables	*N*	Min	Max	*M*	*SD*	Variance	Skewness	Kurtosis
Autistic symptoms	226	17	54.75	31.25	7.77	60.42	0.36	-0.47
General Adaptive Functioning	229	41	130	64.94	14.83	219.82	0.89	1.55
Conceptual Domain	229	45	123	68.51	15.11	228.44	0.50	0.08
Social Domain	229	48	130	70.65	16.58	247.87	0.55	-0.02
Practical Domain	229	41	129	65.55	14.20	201.60	0.63	1.40
Performance IQ	224	47	130	80.08	20.65	426.31	0.18	-1.00
Verbal IQ	223	48	122	72.43	17.28	298.61	0.58	-0.62
Global Language Composite	224	47	117	74.29	19.33	373.73	0.15	-1.07
Annual Income	227	1	5	2.91	1.45	2.09	0.15	-1.07
Age	225	2.50	5.75	4.34	0.47	0.21	-0.83	2.02

Note. Autistic symptoms: raw score on CARS; Adaptive and IQ: standardized scores with mean 100 and standard deviation of 15; Annual income: code 1 = $10,000 to $29,999, 2 = $30,000 to $49,999, 3 = $50,000 to $69,999, 4 = $70,000 to $89,999, and 5 = Over $90,000; age = decimals allowed to record the exact age of the participants (i.e., 2-year-old and 6-month-old is coded 2.5).

Table 2

Summary of Fit Statistics for Different Latent Profile Models

Model	LL	#fp	Scaling	AIC	CAIC	BIC	SABIC	Entropy	Smallest class n (%)	VLMR	BLRT
Conditional independence with equal variance											
1-Class	-6543.97	14	0.933	13115	13129	13164	13119	-	-		
2-Class	-6134.85	22	1.254	12313	12335	12389	12319	.932	41%	.000	.000
3-Class	-6036.63	30	1.298	12133	12163	12236	12141	.880	26.87%	.035	.000
4-Class	-5966.09	38	1.645	12008	12046	12139	12018	.884	15 (6.44%)	.561	.000
5-Class	-5890.94	46	1.320	11873	11919	12032	11886	.899	15 (6.44%)	.042	.000
Conditional independence with unequal variance											
1-Class	-6543.97	14	0.933	13115	13178	13164	13119	-	-		
2-Class	-6032.21	29	1.272	12122	12251	12222	12130	.989	54 (23.17%)	.000	.000
3-Class	-5844.06	44	1.182	11776	11971	11927	11788	.942	48 (20.60%)	.000	.000
4-Class	-5773.13	59	1.094	11664	11926	11867	11680	.911	48 (20.60%)	.000	.000
5-Class	-5718.25	74	1.079	11584	11913	11839	11605	.897	21 (9.01%)	.069	.000

Note. LL: Model LogLikelihood; #fp: Number of free parameters; Scaling = scaling factor associated with MLR loglikelihood estimates; The VLMR test and the BLRT compare the current model to a model with k-1 profiles. LPA = latent profile analysis; AIC = Akaike's Information Criterion; CAIC: Constant AIC; BIC = Bayesian Information Criterion; SABIC = Sample-Adjusted BIC; VLMR = Vuong- Lo-Mendell Ruben; BLRT = bootstrap likelihood ratio test.

Table 3

Classification Table Based on Estimated Posterior Probabilities for the Final Latent Profile Model

	1	2	3	4
1. Mild Impairment with Average IQ	**.94**	.06	.00	.00
2. Mild Impairment with Lower Average IQ	.05	**.94**	.02	.00
3. Moderate Impairment	.00	.02	**.96**	.01
4. Severe Impairment	.00	.00	.01	**.99**

Table 4

Latent Profile Means and Variances on the Mixture Indicators

	Mild Impairment with Average IQ		Mild Impairment with Lower Average IQ		Moderate Impairment		Severe Impairment	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Autistic symptoms	27.65	40.50	25.62	20.87	33.84	23.53	40.14	34.69
Conceptual domain	81.07	173.61	76.72	71.60	60.24	43.31	50.33	14.36
Social domain	80.78	283.27	81.54	82.53	62.76	79.73	51.78	21.52
Practical domain	74.43	208.67	73.74	55.99	60.92	58.97	48.01	25.14
Verbal IQ	94.45	104.81	72.75	74.36	63.41	49.66	52.65	2.12
Performance IQ	101.43	160.19	83.25	145.02	73.44	255.80	55.04	38.03
Global language composite	96.14	98.55	78.53	121.10	64.93	91.68	48.89	5.17

Note. Autistic symptoms: raw score on CARS; Adaptive and IQ: standardized scores with mean 100 and standard deviation of 15.

Table 5

Results from the Multinomial Logistic Regression Evaluating the Effects of Predictors on Latent Profile Membership

Predictors	Mild Impairment with Average IQ vs. Mild Impairment with Lower Average IQ			Moderate Impairment			Severe Impairment		
	Coef. (SE)	OR	95% IC	Coef. (SE)	OR	95% IC	Coef. (SE)	OR	95% IC
Gender	.84 (.73)	2.31	[.55, 9.75]	.30 (.53)	1.35	[.48, 3.83]	.42 (.56)	1.52	[.51, 4.56]
Age	.76 (.67)	2.14	[.58, 7.88]	-.39 (.45)	.68	[.28, 1.64]	-.87 (.52)	0.42	[.15, 1.15]
Income	-.25 (.16)	.78	[.56, 1.07]	-.49 (.17)**	.61	[.44, 0.85]	-.56 (17)***	0.57	[.41, 0.80]

Note. Coef. = Coefficient; SE = Standard error.
*p < .05, **p < .01. ***p < .001

Table 6

Profiles' Distinction on Response to EBI

Outcomes	Mild Impairment with Average IQ	Mild Impairment with Lower Average IQ	Moderate Impairment	Severe Impairment	Summary of significant differences
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	
Autistic symptoms	-1.97 (.02)	-2.03 (.02)	-1.81 (.02)	-1.62 (.03)	2 > 1 > 3 > 4
Slope 1					
Conceptual domain	8.17 (.34)	7.75 (.32)	6.79 (.31)	4.48 (.29)	1 = 2 > 3 > 4
Social domain	6.33 (.07)	6.38 (.05)	5.79 (.06)	5.21 (.04)	2 = 1 > 3 > 4
Practical domain	3.76 (.46)	3.53 (.48)	3.18 (.44)	1.00 (.36)	1 = 2 = 3 > 4
Slope 2					
Conceptual domain	-4.26 (.42)	-3.29 (.34)	0.50 (.21)	2.66(.18)	4 > 3 > 2 = 1
Social domain	-1.26 (.33)	-1.69 (.19)	1.48 (.20)	3.30 (.13)	4 > 3 > 1 = 2
Practical domain	0.90 (.51)	-0.84 (.60)	0.08 (.41)	-0.62 (.27)	1 > 3 = 4 = 3

Note. SE = Standard error; Significant differences are determined by an alpha level of .05.

Figure 1

Elbow Graph of the Information Criteria

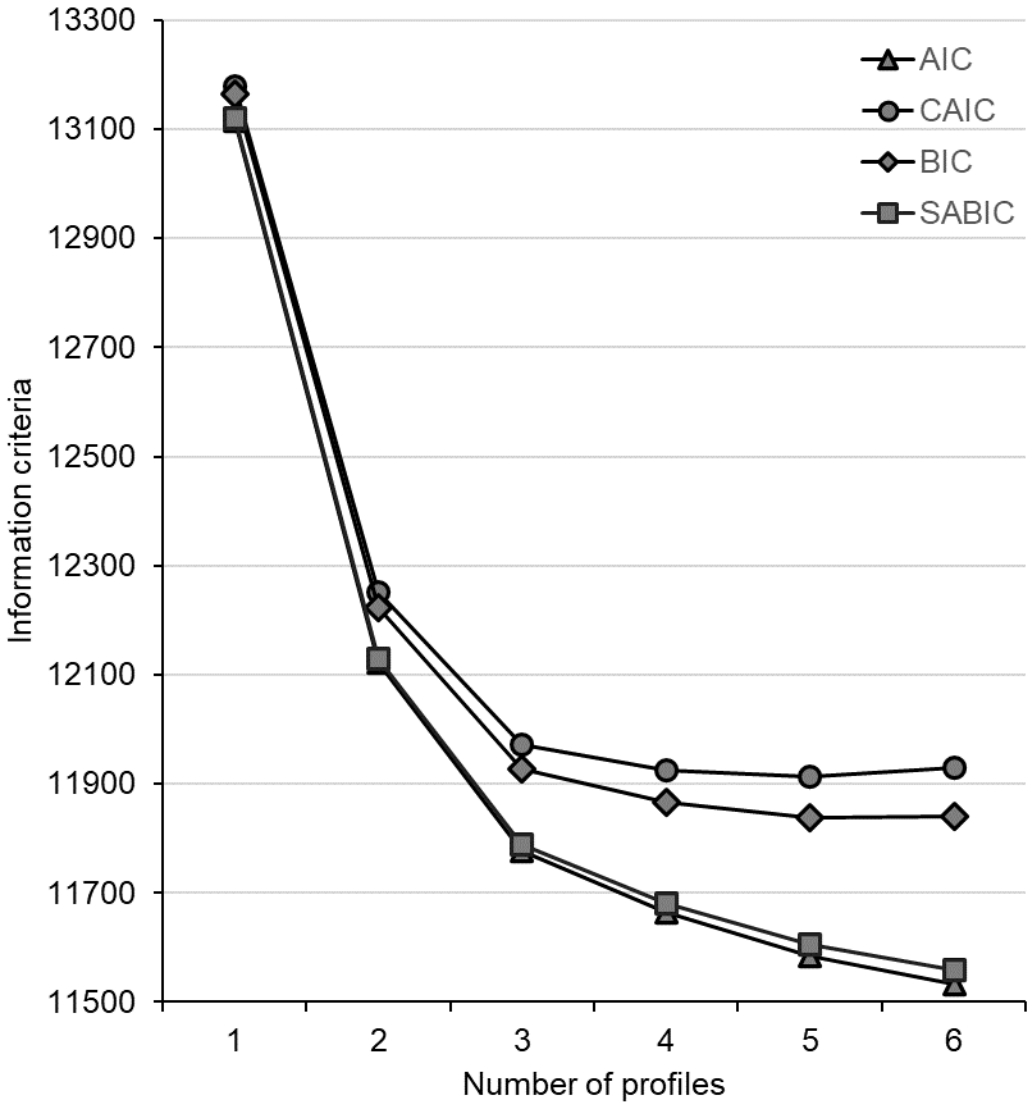

Figure 2

Latent Profile Standard Scores on the Mixture Indicators.

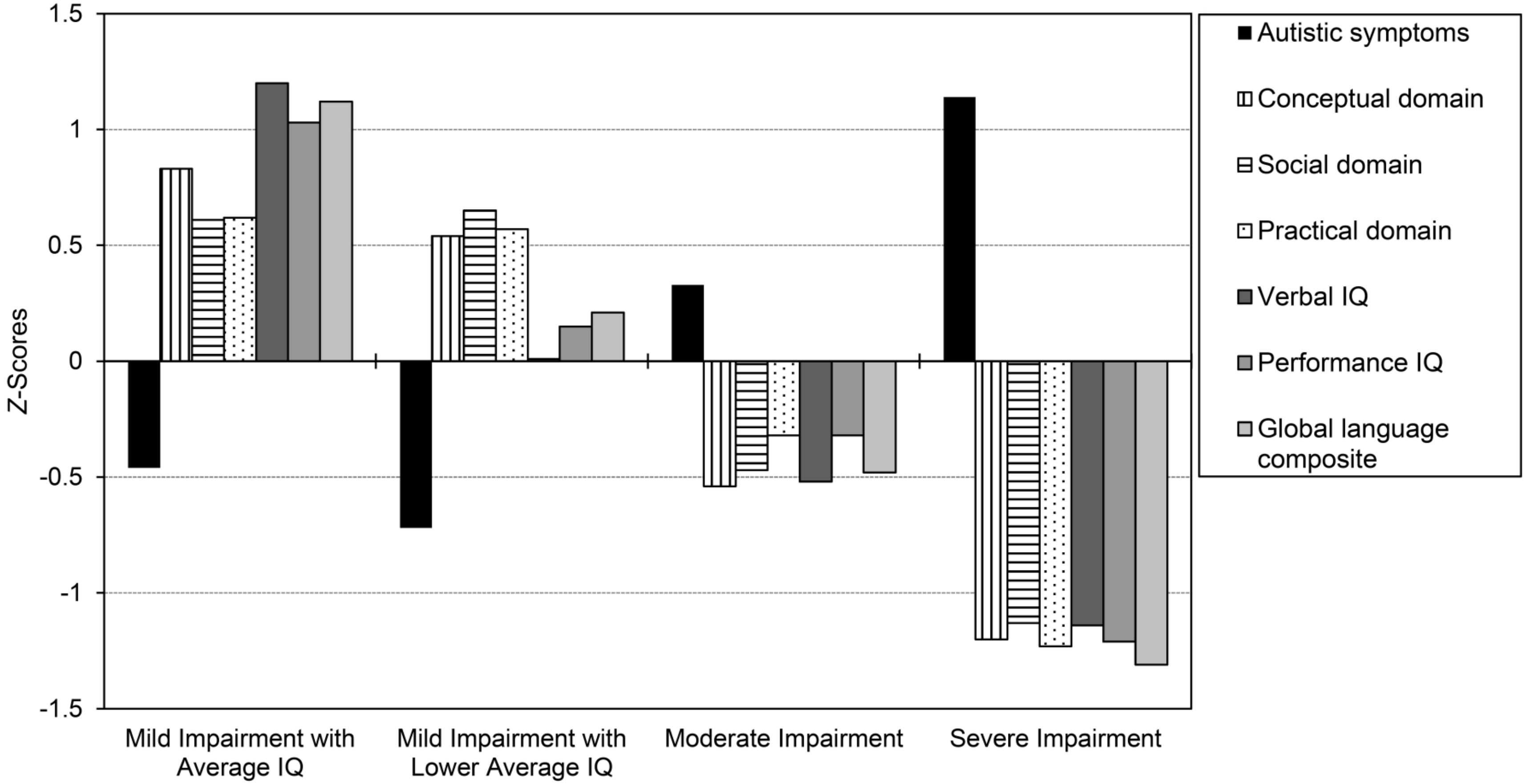

Figure 3

Changes in Autistic Symptoms and the Three Domains of Adaptive Functioning for Each Latent Profile.