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Changes in Autistic Symptoms and Adaptive Functioning of Children Receiving Early Behavioral Intervention in a Community Setting: A Latent Growth Curve Analysis

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Abstract

Despite showing effects in well-controlled studies, the extent to which early intensive behavioral intervention (EBI) produces positive changes in community-based settings remains uncertain. Thus, our study examined changes in autistic symptoms and adaptive functioning in 233 children with autism receiving EBI in a community setting. The results revealed nonlinear changes in adaptive functioning characterized by significant improvements during the intervention and a small linear decrease in autistic symptoms from baseline to follow-up. The intensity of intervention, initial age, IQ and autistic symptoms were associated either with progress during the intervention or maintenance during the follow-up. The next step to extend this line of research involves collecting detailed data about intervention strategies and implementation fidelity to produce concrete recommendations for practitioners.

Keywords: adaptive functioning, autistic symptoms, early behavioral intervention, effectiveness, latent growth curves

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Given that numerous studies and meta-analyses have supported its efficacy (Eldevik et al., 2009; Makrygianni & Reed, 2010; Makrygianni et al., 2018; Peters-Scheffer et al., 2011; Prior et al., 2011; Reichow et al., 2018; Virues-Ortega, 2010; Vismara and Rogers, 2011; Weitlauf et al., 2014), many national health organisations consider early intensive behavioral intervention (EIBI) as an established intervention 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). Researchers have reported positive effects that translate into improvements in cognitive skills, communication abilities, and adaptive functioning (Reichow et al.,2018), but also considered the strength of the evidence as weak, mainly because of nonoptimal study designs and small sample sizes. Some studies have also observed a decrease in autistic symptoms following EIBI (Eikeseth et al, 2012).

Although EIBI generates positive gains for some children with ASD, several researchers point out that the effects vary greatly from one individual to another (Eldevik et al., 2010; Howlin et al., 2009; Magiati et al.., 2011; Prior et al., 2011; Reichow et al., 2018). While some children progress significantly in various areas of development, others make only modest, or even no, improvement on standardized tests (Ben-Itzchak et al., 2014; Dawson et al., 2002; Gabriels et al., 2001; Howlin, 2009; Zachor and Ben-Itzchak, 2010). Heterogeneity in outcomes remains poorly understood; the characteristics of the children which could modulate the efficacy of the intervention, the critical period of intervention, the optimal dosage and the biological markers to identify the candidates most likely to benefit from the intervention are still unknown

(Eapen et al., 2013; Magiati et al., 2012; Reichow et al., 2018). To date, researchers have not identified reliable predictors of EIBI outcomes (Eapen et al., 2013; Reichow, 2012; Smith et al., 2015; Warren et al., 2011). Very few studies on the efficacy of EIBI directly explore moderators of the effects of the intervention (Ben-Itzchak et al., 2014; Eldevik et al., 2010). Knowing the predictors of EIBI outcomes is crucial information for customizing the intervention (Tiura et al., 2017). Moreover, knowledge on how to individualize dosage for children with ASD who present various skills, needs, ages, live in different family contexts is virtually nonexistent (Pellecchia et al., 2019).

Predictors of Efficacy

Some researchers have attempted to identify moderators or mediators associated with the efficacy of EIBI. The most studied variables are age at enrolment, intervention intensity, intellectual quotient (IQ), autistic symptoms, adaptive functioning, and sociodemographic characteristics (Sallows & Graupner, 2005; Klintwall et al., 2015; Perry et al., 2011; Virues-Ortega et al., 2013). The influence of these variables has been examined in different studies and meta-analysis, which sometimes obtain contradictory results. We summarize below the findings on the influence of various predictors on improvement in adaptive functioning, intellectual functioning, language skills and autistic symptoms.

Intervention Intensity

Numerous studies have found that a higher intensity is associated with more gains in adaptive functioning (Eldevik et al., 2010; Linstead et al., 2017; Makrygianni & Reed, 2010; Reed, 2016; Virués-Ortega, 2010). However, results from Fernell et al. (2011) do not support this conclusion. In terms of IQ, some studies indicate the intensity of the intervention is positively associated with improvement in IQ (Eldevik et al., 2010; Linstead et al., 2017;

Makrygianni & Reed, 2010) while others do not find this association (Sallows and Graupner, 2005; Virués-Ortega, 2010). Similarly, the literature does not show consensus on the association between intervention intensity and language gains. Two studies found a positive association (Linstead et al., 2017; Virués-Ortega, 2010) whereas another did not (Makrygianni & Reed, 2010). We identified only one study investigating the association between intervention intensity and improvement in autistic symptoms (Rogers et al., 2021). These authors concluded that intervention intensity did not impact the trajectory of autistic symptoms.

Age at Enrollment

Studies have reported mixed results regarding age at enrollment (Reed, 2016). Some researchers have highlighted the importance of early intervention to maximize the overall effects of the intervention (Granpeesheh et al., 2009; Makrygianni & Reed, 2010; Perry et al., 2013). Results suggest a positive predictive association between age at enrollment and progress in adaptive functioning (Fenske et al, 1985; Makrygianni & Reed, 2010), cognitive gains (Harris and Handleman, 2000; Flanagan et al., 2012; Waters et al., 2020), language (Frazier et al., 2021) and milder autistic symptoms after the intervention (Perry et al., 2011). Despite these results, other studies suggest that age at enrollment does not influence the effects of EIBI (Bieleninik et al., 2017; Eldevik et al., 2006; Virués-Ortega, 2010; Robain et al., 2020).

Intellectual Quotient

Various researchers have studied the influence of IQ on the efficacy of EIBI, with conflicting conclusions. One meta-analysis suggests IQ was not linked to the efficacy of the intervention but would rather be strongly correlated with the post-intervention IQ (Makrygianni & Reed, 2010). In other words, the initial IQ would be associated with the post-intervention IQ, without being associated with the progress made by the child. Thus, both children with a low initial IQ and high initial IQ would benefit from EIBI and would be likely to achieve cognitive gains. Other evidence rather suggests that children with lower initial IQ would have a greater potential for progress, compared to those who already had high IQ level, which risk peaking (Reed, 2016), while some studies found that children with higher initial IQ benefited more from the intervention (Fernell et al., 2011; Harris and Handleman, 2000; Tiruas et al., 2017). To our knowledge, only one meta-analysis has examined the influence of initial IQ on adaptive functioning (Eldevik et al., 2010). The results indicate that initial IQ positively predicts gains in adaptive functioning. Very few studies have directly investigated the link between initial IQ and decrease in autistic symptoms. Ben-Itzchak and colleagues (2014) suggest that there would be no difference in the decrease in autistic symptoms based on initial IQ.

Even though some evidence indicates that verbal and non-verbal IQ have different associations with adaptive functioning and autistic symptoms (Black et al., 2009; Munson et al., 2008), the previous meta-analyses have only investigated the full-scale IQ as a predictor of efficacy. The conflicting findings regarding the influence of IQ on the efficacy of EIBI may reflect a concern that full-scale IQ is too general to uncover more specific aspects of IQ that predict child progress. The influence of the different IQ scales is worth being investigated.

Autistic Symptoms

Again, evidence remains mixed on the possible influence of autistic symptoms on the efficacy of EIBI (Flanagan et al., 2012; Reed, 2016). While some studies suggest that milder autistic symptoms may be associated with better efficacy of EIBI (Ben-Itzchak and Zachor, 2007; Frazier et al., 2021; Sallows and Graupner, 2005; Smith et al., 2000), others did not find this association (Harris and Handleman, 2000), and some even suggest that higher autistic symptoms may be associated with a better response to the intervention (Remington et al., 2007;

Reed and Osborne, 2013). Even though some individual studies have investigated the predictive effect of autistic symptoms, no meta-analysis has yet addressed this question (Reed, 2016). One potential explanation for the observed discrepancy is the lack of uniformity in the instruments used to measure autistic symptoms across studies.

Adaptive Functioning

In contrast, a general consensus has emerged on the influence of initial adaptive functioning. Several 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 and Graupner, 2005; Vivanti, 2014). More specifically, the results of meta-analyses suggest that initial adaptive functioning positively influences the effects of the intervention on language skills and on adaptive functioning itself (Eldevik et al., 2010; Makrygianno and Reed, 2010). A positive association between initial adaptive functioning and post-intervention IQ has also been found (Sallows and Graupner, 2005). That said, no research has examined the interaction between initial adaptive functioning and post-intervention severity of autistic symptoms.

Sociodemographic Characteristics

Certain sociodemographic characteristics were associated with greater success of the intervention, such as high socio-economic status, parental education level, low parental stress, and level of parental involvement in the intervention (Gabriels et al., 2001; Magiati et al., 2011). Moreover, some authors acknowledge that younger age at enrollment (i.e., early entry) may be associated with other factors related to outcome, like parental knowledge and resourcefulness (Perry et al., 2011).

Statistical Methods Used to Evaluate Intervention Effects

When assessing intervention effects in autism, researchers most frequently use single-case experimental designs (Wong et al., 2014; Steinbrennuer et al., 2020). A recent literature review on evidence-based practices for people with autism reported that group designs only represent 23% of the articles included (Steinbrenner et al., 2020). Neither this literature review, nor the previously cited meta-analyses (i.e., Eldevik et al., 2009; Makrygianni & Reed, 2010; Virués-Ortega, 2010; Reichow et al., 2018), explicitly share information about the statistical analyses used to assess intervention effects in group design studies. That said, a brief overview of the included articles indicates that the vast majority used traditional analyses such as ANOVA or linear regression. Despite their usefulness, these traditional analyses rest on a number of assumptions that are either unrealistic or difficult to meet in evaluative research, like the assumptions of compound symmetry, sphericity and homogeneity of variance (Mun et al., 2009; Singer & Willett, 2003).

Recently, researchers in observational studies have begun to employ more contemporary analyses (Caplan et al., 2019; Simonoff and colleges, 2020). One such method is latent growth curve (LGC) analysis. For example, Simonoff and colleges (2020) used LGC in an epidemiological study to estimate the trajectories in autistic symptoms and cognitive ability form childhood to adulthood, while Caplan and colleges (2019) used LGC to assess the relationship between responsive parenting and children’s social skills over time. LGC should also be considered for evaluating intervention effectiveness in group designs in the field of early intervention as it has several advantages over traditional methods (Mun et al., 2009): the advantage of handling measurement errors and individual differences in response to intervention as well as avoiding unrealistic assumptions of traditional analyses mentioned above. Moreover, LGC does not require balanced data; that is, each participant does not need to have the same number of time points, allowing for attrition as long as it remains missing at random or missing completely at random (Singer & Willet, 2003). Finally, LGC can effectively assess intervention efficacy in studies utilizing a pre-post-post design (Mun et al, 2009) and researchers should use these analyses more often.

Effectiveness of Intervention in Community Setting

Most studies on the efficacy of interventions and their predictors have been carried out in a university setting, under highly controlled conditions. The extent to which these results are representative of those that would be achieved by children receiving EIBI in community settings remains uncertain (Flanagan et al., 2012; Perry et al., 2013; Reichow, 2012; Waters et al., 2020). Studies in which the intervention took place in community settings find variable results (Waters et al., 2020), and effects are often smaller (Smith et al.., 2015). Samples are generally small (i.e., 10-30 children) and children are often under the age of 4 (Perry et al., 2013), which is unrepresentative of children receiving services in the community and calls for caution in interpreting this body of results. Furthermore, the majority of EIBI programs were developed in the United States (US; Jones et al., 2011; Rivard et al., 2013) where Board Certified Behavioral Analysts (BCBA) supervise the interventions. These programs may be difficult to adapt and implement in different cultural and linguistic settings (Jones et al., 2011; Rivard et al., 2013).

Notably, the intervention context in Québec, Canada, differs in various aspects from those that have been studied in the past. Since the Ministerial orientations published in 2003 by the Québec's Department of Health and Social Services, regional readaptation centers must provide EIBI to children aged from 2 to 5 with ASD (MSSS, 2003). The first major dissimilarity resides in the training of the personnel who implement the intervention. Unlike American universities, Quebec universities do not have bachelor's or master's programs in applied behavior analysis, which limits the number of behavior analysts available. According to the Behavior Analyst Certification Board, Canada counts 1861 certified behavior analysts, with only 56 in Quebec (BACB, 2021). This number is low considering that Québec comprises more than 20% of the Canadian population. Intervention is therefore implemented by special education technicians[1] that received a different training. Most of them have a college degree in special care counselling and are supervised by a psychologist (doctoral degree) or a psychoeducator (master's degree) who rarely have formal training in behavior analysis (see Mello et al., 2018 for description).

The second important difference lays in the dosage of the intervention offered. While most studies included in the cited meta-analysis offered high intensity intervention, the number of hours offered weekly in Quebec is low-to-moderate when compared to the United States and varies across different geographic areas, as each regional readaptation center is responsible to organise their service offer. In many cases, the intensity may not qualify the intervention as being "intensive". Hence, we will use the expression early behavioral intervention (EBI) to refer to their program to prevent misleading the reader. The last particularity of the Quebec context is the accessibility. In some regions, waiting lists to access diagnostic assessment and access EBI are long (more than 1 years), which results in children being older when they start receiving intervention. As preschool starts at 5 years old, this delay implies that children receive the intervention for a relatively short period of time. Therefore, the purpose of our study was to (1) evaluate the effects of a community-based intervention program as offered by a regional readaptation center in Quebec, Canada, (2) determine whether the effects were maintained at the 1-year follow-up, and (3) identify potential predictors of effectiveness.

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

Method

Participants and Procedures

This study consists of secondary analyses of data from an assessment of the effectiveness of a community-based intervention program conducted among an unselected community sample that took place from 2009 to 2012. The sample included 233 children (78.6% boys) diagnosed with ASD aged between 2.50 to 5.75 years old (M = 4.34, SD= 0.47) who received one of the two early behavioral intervention options. Participants were divided between the intervention options in the following proportion: 53.9% of participants received low-intensity intervention and the remaining 46.1% received moderate-intensity intervention (see intervention description below). This study is the first to combine the two intervention options; previous papers only analysed data for the moderate-intensity option.

Given that the detailed procedures were reported elsewhere (Rivard et al., 2014, Rivard et al., 2019), we only provide a summary here. We used a prospective longitudinal design with three annual assessments. 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). Because the intervention took place the year before entering preschool for the majority of our sample, attrition at time 3 may be the result of children no longer receiving services from the readaptation center, making them harder to reach for the completion of the 12-months follow-up. To be eligible for the intervention and the study, children needed (1) to have a diagnosis of ASD provided by a pediatric psychiatrist and independently confirmed by a multidisciplinary team, (2) to be aged 5 years old or younger, and (3) to live within the geographical area served by the rehabilitation center. In addition, (4) parents had to provide written consent to participate in the study. The Joint Research Ethics Board for Readaption Centres in Québec approved the research project.

Early Behavioral Intervention Program

The study took place in a rehabilitation center providing developmental services to persons with an intellectual disability, ASD, or both in a large catchment area with a suburban and rural population of 847,422 (at the time of the study) located un the South Shore area near Montreal, Quebec, Canada. This public agency provided intervention based on applied behavior analysis. Their program was mostly based on the work of Lovaas and Maurice (Lovaas, 1981; Maurice, Green, & Luce, 1996) and adopted a 1:1 child-to-educator ratio. Generally, two special education technicians alternated working directly with the child. The special education technicians implemented the intervention in the child's natural environment, usually at home or in a childcare setting.

Every two weeks, a clinical advisor or a psychologist responsible for this service provided supervision to the special education technicians. Intervention objectives were individualized for each child according to their baseline evaluation. These objectives primarily targeted basic (e.g., eye contact, attention to task), social (e.g., communication, social interaction) and cognitive (e.g., school-type tasks) skills. The special education technicians used mostly a combination of two teaching strategies: discrete trial teaching and incidental teaching. Discrete trial teaching refers to the repetitive use of the stimulus-response-consequence sequence to teach a behavior, while incidental teaching implies structuring the environment in order to provide learning opportunities (Paquet et al., 2012). The rehabilitation center offered two intensity intervention options: low-intensity (i.e., between 4 and 12 hours weekly) and moderate-intensity (i.e., between 16 and 20 hours weekly). The intensity option was determined based on the center's evaluation of the children needs at enrollment in the services, and the preferences and availability of the parents (see Rivard et al., 2014, 2019 for more details about the intervention).

Measures

Autistic Symptoms

The *Childhood Autism Rating Scale 2* (CARS-2; Scholper et Van Bourgondien, 2010) was used to assess the participants' autistic symptoms. The CARS-2 contains 15 items assessing behavior on a 4-point scale from one to four (1 = normal, 4 = severely abnormal). Half points can be scored if the child's symptoms are between two anchor points. Items assess different apparent difficulties in children with ASD (i.e., social relations, imitation, emotional responses, use of body, use of objects, adaptation to change, visual responses, auditory responses, taste/smell/touch, fear and anxiety, verbal communication, nonverbal communication, level of activity, intellectual functioning, and general impression). The scores range between 15 and 60, with higher scores indicating more severe autistic symptoms. The CARS-2 has an excellent internal consistency ($\alpha = .93$) in children aged 0 to 6 years and very good test-retest reliability ($r = .88$; Scholper and Van Bourgondien, 2010). In the present study, the CARS-2 was completed by a parent and a special education technician. As both informants were highly correlated ($r = .67 - .81$ depending on time point), we used the average score between the two respondents.

Adaptive Functioning

We used the *Adaptive Behavior Assessment System-II* (ABAS-II; Harrison and Oakland, 2003) to assess adaptive functioning, more precisely the parent/primary caregiver form for children aged 0-5 years old. 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 ABAS-II results provide a score for each of the three domains recognized by the American Association for Intellectual and Developmental Disabilities (Schalock et al., 2010) as necessary to assess adaptive behaviors, namely the conceptual, social, and practical domains. The ABAS-II also provides a general adaptive composite score based on the three aforementioned domains. The ABAS-II has demonstrated excellent internal consistency for general adaptive functioning (α = .98 - .99) and the three adaptive domains (α = .90 - .98), as well as very high test-retest reliability (r = .90; Harrison & Oakland, 2003).

Intellectual Functioning

The *Wechsler Preschool and Primary Scale of Intelligence* (WPPSI-III; Wechsler, 2003) was used to measure intellectual functioning. The WPPSI-III consists of 15 sub-tests, which are in turn grouped into five dimensions: verbal comprehension, visuospatial performance, fluid reasoning, working memory and information processing speed. Depending on the child being assessed, test administration lasts between 45 and 105 min. The results provide scores for the verbal IQ, the performance IQ, the general language composite, and the full-scale IQ. In the present study, only the verbal IQ, performance IQ and general language composite were considered because they provide more specific information than the full-scale IQ. The scale's internal consistency ranged between .83 and .95 across subtests and .89 and .96 across composite scores. Test–retest reliability coefficients were .87, .81, .88, and .88 for the verbal IQ, performance IQ, full-scale IQ, and general language composite, respectively. Inter-rater reliability ranged between .98 and .99. In this study, the WPPSI-III was administered by research assistants who were psychology graduate students supervised by the head of the research team, a psychologist and a university professor.

Program Intensity

Program intensity was a dichotomous variable. The response options were: 0 = low-intensity intervention or 1= moderate-intensity intervention.

Age at Enrollment

Age was a continuous variable. We used decimals to collect the exact age of the participants. For example, a 2-year-old and 6-month-old would have a score of 2.5 years.

Annual Income

Annual income was an ordered-categorical variable. We asked the participant's parents the following question: "What is your annual family income?" The response options were: 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.

Statistical Analyses

Descriptive Statistics and Attrition Analyses

We performed preliminary analyses using SPSS 26.0, which involved descriptive (i.e., frequencies, mean, measure of dispersion) and correlational statistics. Considering the high attrition at the third assessment, we made attrition analyses using Little's missing completely at random test, followed by Chi-square tests (for categorial variables) or ANOVAs (for continuous variables) when significant to verify if any of the sociodemographic characteristics were associated with attrition.

Latent Growth Curve Analyses

Using Mplus 8.3 (Muthén & Muthén, 2017), we conducted LGC analyses within the structural equation modelling framework (Bollen & Curran, 2006) to estimate changes in autistic symptoms, general adaptive functioning, and the conceptual, social, and practical domains of adaptive functioning of the participants. LGC analysis estimates change through latent variables (i.e., unobserved variables; see Bollen & Curran, 2006; Curran et al., 2010). The objective was to determine the shape of the trajectory for the sample that is *a priori* unknown. The analysis begins by estimating an individual growth curve for each child. Then, the program estimates the average growth factor parameters, namely an intercept (i.e., the average score at T1) and a slope (i.e., expected amount of change over time). The variances of these growth factor parameters are also estimated, which represent the differences between individuals. Thus, LGC estimate interindividual differences in intra-individual change (Little, 2013; Stull et al., 2011). Another interesting aspect of LGC within the structural equation modelling framework is that it is straightforward to include categorical or continuous predictors of the intercept and slope parameters (Curran et al., 2010; Little, 2013).

We estimated separate models for five outcome variables (autistic symptoms, general adaptive functioning, conceptual domain, social domain, practical domain). Because of the small sample size and attrition, we followed the recommendation of using the maximum likelihood robust estimator (MLR; Shi et al., 2021). This estimator essentially corrects the standard errors and chi-square tests for non-normality in the data. We dealt with missing data using full-information maximum likelihood estimation, which allow to use every case in the sample and provide unbiased parameters estimates, even in the presence of large attrition (see Enders, 2010; Little, 2013).

To determine the best growth model for each outcome, we followed a model-building procedure proposed by Preacher et al. (2008), where a series of nested LGC models is specified in a predetermined sequence, starting with an intercept-only without variance model and gradually increasing in complexity, while comparing the model fit. Our analyses sequentially estimated the following models for all outcome variables to determine the best shape of the trajectory in the data: Model 0 = fixed intercept (no variance), Model 1 = a random intercept, Model 2 = a random intercept and a fixed slope, Model 3 = a random intercept and a random slope, Model 4 = a random intercept, a random slope and imposed homoscedasticity of the residuals. We also estimated models with autocorrelations of the time-specific residuals across time, but they were not retained in any models, as either the autocorrelations were not significant, or it resulted in out-of-bound parameters (i.e., negative variance). Even though we only had three time points, it was important to test for potential nonlinear change in the growth curves in order to determine if the nature of the change was different during the year after the intervention has ended. In principle, only a linear model can be estimated with three time points (for instance, a quadratic slope cannot be estimated because it is not statistically identified), but alternative specifications are possible to test for nonlinearity (see Bollen & Curran, 2006).

Consequently, Model 5 tested the nonlinearity of the growth curves by estimating latent basis models (LBM), where the first two loadings of the slope are fixed at 0 and 1, while the last loading was freely estimated (Bollen & Curran, 2006). In such model, a significant increase in model fit paired with a third estimated loading largely different from the value expected for a linear trajectory (in this case, a loading of 2) suggests presence of nonlinear change. When nonlinearity was detected using LBM, we used a piecewise growth modeling (PWGM; Kamata et al., 2013) in Model 6 to estimate an intercept and two slopes; the first slope captures change between time 1 and time 2 (slope 1), while the second slope captures change between time 2 and time 3 (slope 2). The resulting PWGM is a saturated model (i.e., with no degree of freedom and perfect fit), but it has the distinct advantage of providing an estimate of two different slopes and regressing predictors on these two different slopes to determine whether predictors are associated to different phases of change.

To produce a PWGM that was identified with only three time points, we followed the model specification suggested by Kamata et al. (2013). Finally, we modeled conditional LGC in Model 7 by including time-invariant exogenous predictors of the intercept and slopes. For all conditional models, predictors were age at enrolment, intensity of intervention, family annual income, verbal IQ, performance IQ, general language composite. We added general adaptive functioning as a predictor for the autistic symptoms model, and we added autistic symptoms as a predictor for the general adaptive functioning, conceptual, social and practical models.

Model Fit. In the structural equation modelling framework, various statistical tests and fit indices are used to determine to what extent the model-implied covariance-matrix adequately reproduced the observed data (see West et al., 2012). For absolute fit, Mplus report the chi-square test, the root mean square error of approximation (RMSEA) and the Standardize Root Mean Square Residual (SRMR). A non-significant chi-square test, an RMSEA value under .6 and a SRMR value under .08 indicate good fit of the model to the data (Hu & Bentler, 1999). For comparative fit, Mplus reports the comparative fit index (CFI) and the Tucker-Lewis index (TLI). CFI and TLI values under .95 indicate excellent fit to the data (Hu & Bentler, 1999), but values of at least .90 still indicate acceptable fit (Little, 2013). Three Information criteria used to compare different models are also calculated, namely the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the sample-size adjusted Bayesian information criterion (SABIC). Lower values of AIC, BIC and SABIC indicate a better fitting model. To compare nested models, we used the Satorra-Bentler adjusted chi-square test suitable for the MLR estimator, as well as the difference in RMSEA (ΔRMSEA) and CFI (ΔCFI). A significant Satorra-Bentler asjusted chi-square test indicates that the compared models provide significantly different fits to the data (Satorra, 2000). A difference in RMSEA smaller than 0.015 suggests that there is no significant difference between models (Chen, 2007), while a difference in CFI greater than 0.02 indicates a significant difference between models (Cheung and Rensvold, 2002).

Results

Descriptive Statistics and Attrition Analyses

Table 1 presents the descriptive statistics. Given that intervention option was determined based on the evaluation of the children needs, we provide descriptive information for each intensity option in the online supplements (see Table S1). For the attrition analyses, Little's missing completely at random test was nonsignificant for autistic symptoms, but was significant (p = .029) for the constructs measured by the ABAS-II, namely general adaptive functioning, conceptual, social and practical domains. This result suggested that attrition was not completely random; however, chi-square tests and ANOVAs comparing the scores of children who were lost to attrition to those who were not were all nonsignificant. Therefore, we approximated a missing at random pattern and the use of the robust maximum likelihood estimator is adequate.

LGC Analyses

Model Selection

The various fit indices indicated that, for all outcomes considered in this study, the addition of parameters in the models up to a linear slope with a variance resulted in significant improvement in fit to the data; for lighten the presentation, Table S2 in the online supplements presents the fit indices for Model 0 to 3, while Table 2 presents the fit indices for subsequent Models 4 to 7. For autistic symptoms, the best fitting unconditional model was Model 4 (i.e., random intercept, random slope, and homoscedasticity of residuals). All the fit indices suggest this model provided good fit to the data. Testing nonlinearity of the trajectory in Model 5 (i.e., LBM), inspection of the freed loading clearly suggested linear changes in autistic symptoms.

For three of the variables linked to adaptive functioning (general adaptive functioning, conceptual domain, social domain), Model 5 (i.e., LBM) fitted significantly better than the linear change model. In addition to improved fit, inspection of the freed loadings clearly suggested nonlinearity over time. For the practical domain of adaptive functioning, inspection of the fit indices did not allow distinguishing the linear model from the non-linear model with certainty, but visual inspection of the observed trajectory suggested possibility of nonlinear change, so we estimated Model 6 (i.e., PWGM) to inspect the slopes. For all four variables, Model 6 (i.e., PWGM) confirmed nonlinearity by estimating different values for slope 1 (T1 to T2) and slope 2 (T2 to T3). Model 6 is saturated; therefore, the fit of this model can only be compared to previous models using the information criteria. We observed large reductions in AIC, BIC and SABIC comparing this model to Model 4 (i.e., linear growth), but trivial differences compared to Model 5 (i.e., LBM), which confirmed the adequacy of Model 6 (i.e., PWGM). Figure 1 shows the plotted observed and model-implied (predicted) scores for the four variables of adaptive functioning.[2] Visual inspection reveals a deceleration between T2 and T3, which is consistent with nonlinearity, similarly to the estimation of two different slopes in the Model 6 (i.e., PWGM). As for the practical domain, it may appear more linear than the other variables' trajectories, but it is mostly because it has the smallest slope, followed by stability like the other domains. Figure 1 also shows that the predicted trajectories of the final selected model followed closely the observed trajectory.

Growth Parameters

Table 3 presents the growth parameters for all the final models for the four outcome variables. Readers can use the spreadsheet available on the online supplements to compare their

[2] In order to provide estimates of uncertainty for the mean scores across time, Table S3 available in the online supplements provides residual variances for Model 6 at each time points.

data with our average estimated trajectories. For autistic symptoms, the final unconditional model (Model 4) reveals that the intercept and its variance were statistically significant, suggesting that autistic symptoms varied between children at baseline. The slope was also significant, which indicates that autistic symptoms significantly decreased linearly over time. The decrease represents about a quarter of a standard deviation for this variable. The slope variance was not significant, indicating that the autistic symptoms decreased at approximately the same rate for all children in the sample. The intercept and slope were not correlated in this model.

For all the variables linked to adaptive functioning, the final unconditional models (Model 6) indicate the intercepts and their variance were statistically significant. In other words, general adaptive functioning and the conceptual, social, and practical domains varied between children at baseline. Their slope 1 were also significant and suggest that the four variables increased during the intervention period (i.e., T1 to T2). General adaptive functioning and the conceptual and social domains increased for about a third of the standard deviation for those variables, while the practical domain increased for about a fifth of its standard deviation. All slope 1 variances were not significant, meaning that, on average, children progressed at the same rate. For all four variables, their slope 2 were not significant, indicating that, on average, general adaptive functioning and the conceptual, social, and practical domains remained stable during the period following the intervention (i.e., T2 to T3). For the practical domain, the slope 2 variance was significant, which merely suggests that there was variability between children in the stable level of practical scores between during the follow-up period. Looking at the correlations between the intercepts and the slopes, the only significant correlation is between the intercept and the slope 2 for the conceptual domain. Since slope 2 was not significant (stability over time), this correlation merely suggests that conceptual level at baseline was significantly correlated with conceptual level during the period following the intervention.

Predictors of Growth Parameters

Table 4 presents the coefficients for the predictive relations estimated from the conditional models (Model 7). Each coefficient represents the simple effect of a given predictor, holding all other variables constant. For autistic symptoms, general adaptive functioning and age at baseline negatively predicted the intercept, meaning that younger children and children with lower general adaptive functioning also had more severe autistic symptoms at baseline. Two other predictors almost reached the typical criteria for statistical significance. First, program intensity was negatively related to the slope, which suggests that autistic symptoms scores tended to decrease more slowly for children who receive less intense intervention. Second, general language composite positively predicted the slope, implying that children with higher general language composite scores at baseline tend to show more rapid decreases in autistic symptoms over time.

For general adaptive functioning, autistic symptoms negatively predicted the intercept and slope 1, meaning that children with higher autistic symptoms tended to have lower general adaptive functioning scores at T1 and to show smaller increases in general adaptive functioning during the intervention period. Program intensity marginally predicted the intercept. The association is negative, which is not surprising considering that program intensity was determine based on the evaluation of the children needs at enrollment in the services. Thus, children who were assigned low-intensity intervention were more likely to have higher general adaptive functioning at baseline. Age at enrolment negatively predicted slope 2, which was not significant, implying that younger children tended to have higher stable general adaptive functioning level during the period following the intervention. Performance IQ also marginally predicted slope 2, which merely suggests that children with higher performance IQ were more likely to maintain their general adaptive functioning level between T2 and T3.

For the conceptual domain of adaptive functioning, autistic symptoms negatively predicted the intercept. Thus, children with higher autistic symptoms were also more likely to have lower conceptual score at T1. Family income, performance IQ and general language composite positively predicted the intercept. These results suggest that children in families with higher income, higher performance IQ and general language composite were also more likely to have higher conceptual functioning scores at T1. Autistic symptoms also negatively predicted slope 1, meaning that children with higher autistic symptoms at baseline tended to show slower increases in conceptual scores during the intervention period. Age at enrolment negatively predicted slope 2, indicating that younger children tended to have higher stable conceptual level during the period following the intervention. For the social domain of adaptive functioning, autistic symptoms negatively predicted the intercept, implying that children with higher autistic symptoms also had lower social scores at T1. General language composite negatively predicted slope 2, suggesting that children with lower general language composite at baseline tended to maintain their higher stable social level during the period following the intervention.

Finally, autistic symptoms negatively predicted the intercept and slope 1 for the practical domain, meaning that children with higher autistic symptoms also had lower practical functioning at T1. Also, the participants made less improvement regarding the practical functioning during the intervention period. Age at enrolment negatively predicted slope 2, which is not significant, which again suggest that younger children tended to show higher stable practical level during the period following the intervention. Lastly, performance IQ predicted slope 2, implying that children with higher performance IQ at baseline also tended to have higher stable practical level during the period following the intervention.

Discussion

Each of our initial objectives produced results that contribute to our knowledge base on early behavioral intervention. All the variables linked to adaptive functioning (general adaptive functioning, conceptual domain, social domain, practical domain) increased during the intervention period (i.e., between T1 and T2), but became stable during the period following the intervention (i.e., between T2 and T3). At this point, it should be noted that the majority of the participants had entered school at the moment of T3. The increase in scores during the intervention period, followed by stability during the period after the intervention, implies that when we interrupt the intervention, the children stop progressing, but maintain their gains. This observation is consistent with a previous finding indicating that EBI has positive effect on adaptive functioning (Reichow et al.,2018). Looking at the three domains of adaptive functioning, our results showed that scores on the practical domain increased at a slower rate during the intervention than the conceptual and social domains. Another peculiarity of the practical domain was that slope 2 was not significant (no change during the follow-up period), but its variance was, which merely suggests that there was variability between children in the level of practical domain during the period following the intervention. Because the latent variable slope is an average, a nonsignificant slope with a significant variance may imply that the practical domain score increased for some children while decreasing for others. Subsequent studies should use mixture modeling to help uncover this possible phenomenon.

We observed small but steady changes in autistic symptoms across all three time points. As there is no significant difference in the rate of change between the intervention period and the period following the intervention, it is unclear whether the intervention is related to the decrease in autistic symptoms. Nevertheless, our results suggest that adaptive functioning may improve even when the severity of autistic symptoms decreased marginally. This result is consistent with a recent meta-analysis suggesting that autistic symptoms are notably stable over time across childhood and that intervention studies should also consider improvement in adaptive functioning (Bieleninik et al., 2017). We chose to evaluate the effectiveness of EBI using scores on standardized measures. Some authors argue that standardized scores may underestimate the individual progress for some children receiving the intervention (see Klintwall et al., 2015). Those authors have shown that even small improvements on standardized scores may narrow the gap between children with autism and their typically developing peers when looking at age-equivalents rather than standardized scores (Klintwall et al., 2015). As such, the CARS scores may not be the best measure to assess intervention effectiveness on autistic symptoms.

Regarding predictors of effectiveness, various variables were associated with progress during the intervention and maintenance during the follow-up periods. Autistic symptoms decreased more slowly for children who received less intensive intervention, and more rapidly for those who had a higher general language composite at baseline. As program intensity was determined by the evaluation of each child’s needs, this association may be the result of attrition to the mean. General adaptative functioning tended to increase more slowly for children with higher autistic symptoms. Younger children and children with higher performance IQ were more likely to maintain their gains in general adaptive functioning. Conceptual domain scores increased more slowly for children with higher autistic symptoms, and younger children tended to have higher stable conceptual level during the period following the intervention. No variable was associated with increase the in social domain during the intervention period, but children with lower general language composite scores maintained their high stable social level during the period following the intervention. Practical domain scores increased more slowly for children with higher autistic symptoms. Younger children and children with higher performance IQ were more likely to show higher stable practical level during the period following the intervention.

Despite a marginally significant association with reductions in autistic symptoms, intervention intensity did not predict improvements in adaptive functioning (i.e., general adaptive functioning, conceptual domain, social domain, practical domain). One potential explanation is that both intervention options were far below the 40 hr per week Lovaas suggested in his original work (Lovaas, 1981). Therefore, optimal progress may have been more difficult to achieve. Another potential explanation lies in the study design. As we used a correlational design, we did not have a high level of control over each variable. The influence of intervention intensity may not have been detectable. One possible variable that may have interacted with the intervention intensity is intervention fidelity, as suggested by Pellechia et al. (2019). The intervention was individualized according to an initial needs assessment. Children with more severe symptoms of autism received more intensive intervention, while children with less severe symptoms received less intensive intervention. The non-random group attribution between the low-intensity and the moderate-intensity intervention limits the inferences we can make about the influence of intervention intensity on the effectiveness of EBI.

The main limitation of this study is the absence of a control group. We used a correlational design, with only one time point before intervention implementation. Such design limits the causal inferences between the intervention and the observed change, and do not allow to control for maturation effects. Lack of control group is common in early intervention research, as many consider it would be unethical to assign children with a neurodevelopmental condition to a control group for a long time during a critical developmental period (Matson, 2007). Another limitation concerns the raters assessing outcomes (i.e., adaptive functioning and autistic symptoms), who were the special education technicians implementing the intervention and the parents, which could have induced bias. Future research should opt for more rigorous group designs, such as a regression discontinuity design, waiting list design or randomized control trials and, blind raters to assess intervention outcomes to better demonstrate the impact of the intervention (Steinbrennner et al., 2020; Shadish et al., 2002). Another limitation relates to the absence of a measure of implementation fidelity and of the quality of the supervisions offered to the special education technicians. Those critical aspects can influence intervention effectiveness (DiGennaro et al., 2007; Durlak et DuPre, 2008), especially because the training of the special education technicians who implemented the intervention differed from the training of technicians in other countries. For example, errors in the integrity of the treatment, especially in the way of providing reinforcement, would influence the effectiveness of the intervention (Bottini et al., 2020). Likewise, the quality of supervision received by special education technicians would influence their implementation of the intervention (Davis et al., 2002). Beyond the characteristics of the children, implementation fidelity may be partly responsible for the effects of the intervention (Klintwall et al., 2015). Future large-scale community-based studies should collect detailed data about intervention strategies and implementation fidelity so that results could have practical implications on how to make the best intervention for children with autism.

Our sample size was not ideal as larger sample sizes produce more trustable estimates in the structural equation framework (Little, 2013). Nonetheless, simulation studies evaluating the reduction of standard errors for sample size between 40 and 500 suggest that between 40 and 100, the standard errors decrease quickly, while the rate of error reduction transitions from rapid to slow between 100 to 150 (Little, 2013). Finally, we had high attrition during the follow-up period. Nonetheless, growth models can be estimated in the presence of partially missing data when data are missing completely at random or missing at random (Curran et al., 2010). Our verifications indicated that the data in our sample were missing at random and that the use of maximum likelihood robust estimator was adequate and allowed us to estimate the models despite the presence of large attrition (Enders, 2010; Little, 2013). Future research should opt for group designs with larger sample sizes and use a retention strategy to prevent high attrition.

Our study contributes to the knowledge base on the effectiveness of EBI. The results revealed nonlinear changes in adaptive functioning characterized by significant improvement during the intervention period and a small linear decrease in autistic symptoms from baseline to follow-up. In addition, intensity of intervention, age at enrolment, IQ and autistic symptoms were either associated with progress during the intervention period or maintenance during the follow-up period. Taken together, these results underline the importance of conducting further replications in community settings. In terms of methodological contribution, this study is one of the few to use more contemporary statistical analyses, which have many advantages over more traditional analyses to assess intervention effectiveness. Our results could thus encourage other researchers to integrate these analyses in their future work.

Compliance with Ethical Standards

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Ethical Approval: All procedures performed in this study were in accordance with the ethical standards of the Canadian Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans and with the 1964 Helsinki declaration and its later amendments.

Informed Consent: Parents provided informed consent for them and their child.

Conflict of Interest: The authors have no conflict of interest to report.

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Table 1

Descriptive Statistics

Variable	*N*	Min	Max	M	SD	Skewness	Kurtosis
GAC T1	229	41	130	64.94	14.83	0.89	1.55
GAC T2	219	40	125	70.31	18.06	0.18	-0.64
GAC T3	64	40	113	70.87	18.43	0.47	-0.36
CON T1	229	45	123	68.51	15.11	0.50	0.08
CON T2	219	45	121	74.78	17.41	0.01	-0.87
CON T3	64	45	109	74.69	16.40	0.01	-0.73
SOC T1	229	48	130	70.65	16.58	0.55	-0.02
SOC T2	219	48	121	75.78	18.67	0.05	-0.92
SOC T3	64	48	125	78.05	17.74	0.48	-0.05
PRA T1	229	41	129	65.55	14.20	0.63	1.40
PRA T2	29	41	126	67.92	16.36	0.23	-0.10
PRA T3	64	40	116	68.59	19.90	0.52	-0.67
AS T1	226	17	54.75	31.25	7.77	0.36	-0.47
AS T2	152	17	55	29.58	7.48	0.91	1.15
AS T3	56	15	49	26.86	8.04	0.67	-0.29
Program Intensity	230	0	1	0.46	0.50	0.16	-1.99
PIQ	224	47	130	80.08	20.65	0.18	-1.00
VIQ	223	48	122	72.43	17.28	0.58	-0.62
GLC	224	47	117	74.29	19.33	0.15	-1.07
Annual Income	227	1	5	2.91	1.45	0.15	-1.07
Age at T1	225	2.5	5.75	4.34	0.47	-0.83	2.02

Note. GAC = General Adaptive Composite; CON = Conceptual Domain; SOC = Social Domain; PRA = Practical Domain; AS = Autistic Symptoms; PIQ = Performance Intellectual Quotient; VIQ = Verbal Intellectual Quotient; GLC = Global Language Composite; T1 = Time 1, T2 = Time 2; T3 = Time 3.

Table 2

Model Fit Indices for the Latent Growth Curve Models

Models	Mod. Ref.	x^2	dl	RMSEA	[90%CI]	SRMR	CFI	TLI	AIC	BIC	SABIC	$\Delta S\chi^2$	Δ dl	ΔCFI	ΔRMSEA
Severity of Autistic Symptoms															
Model 4	3	2.572	3	.000	[.000, .105]	.073	1.000	1.003	2837	2857	2838	+2.384	2	0	0
Model 5	4	2.041	4	.000	[.000, .072]	.104	1.000	1.010	2834	2851	2835	-	-	0	0
Model 6	-	-	-	-		-	-	-	-	-	-	-	-	-	-
Model 7	4	15.099	12	.036	[.000, .084]	.048	.990	.979	2355	2415	2358	-	-	-.021	-.036
General Adaptive Functioning															
Model 4	3	38.046***	3	.224	[.164, .291]	.128	.859	.859	4111	4132	4113	+21.383***	1	-.081	+.044
Model 5	3	2.067	1	.068	[.000, .202]	.096	.996	.987	4086	4113	4088	-12.953***	1	+.056	-.112
Model 6	5	-	0	0	[-]	.000	1.000	1.000	4086	4117	4089	-	-	+.004	-.068
Model 7	6	-	0	0	[-]	.000	1.000	1.000	3385	3484	3389	-	-	.000	.000
Conceptual Domain															
Model 4	3	26.891***	3	0.185	[.125, .252]	.104	.884	.884	4095	4115	4096	-.048	1	+.011	-.052
Model 5	4	10.986***	2	0.139	[.067, .224]	.152	.956	.934	4079	4103	4081	-11.972	1	+.050	-.046
Model 6	5	-	-	0	[.000, .000]	.000	1.000	1.00	4076	4107	4079	-	-	+.044	-.139
Model 7	6	-	-	0	[.000, .000]	.000	1.000	1.00	3366	3466.	3371	-	-	.000	.000
Social Domain															
Model 4	3	6.804	3	.074	[.000, .149]	.052	.973	.973	4184	4205	4186	-.023	1	+.013	-.036
Model 5	4	2.080	4	.000	[.000, .072]	.136	1.000	1.010	4175	4193	4177	-	-	+.027	-.074
Model 6	5	-	0	.000	[.000, .000]	.000	1.000	1.000	4181	4212	4183	-	-	0	0
Model 7	6	-		.000	[.000, .000]	.000	1.000	1.000	3515	3614	3519	-	-	0	0
Practical Domain															
Model 4	3	4.203	3	.042	[.000, .125]	.067	.995	.995	4042	4063	4044	+.270	1	-.001	-.004
Model 5	4	5.019	2	.081	[.000, .172]	.068	.988	.981	4044	4068	4046	+.001	1	-.007	+.039
Model 6	5	-	0	.000	[.000, .000]	.000	1.000	1.000	4044	4075	4047	-	-	+.012	-.081
Model 7	6	-	0	.000	[.000, .000]	.000	1.000	1.000	3395	3495	3400	-	-	.000	.000

Note. χ^2 = chi square; df = degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; 90% CI = 90% Confidence Interval of the RMSEA; SRMR = Standardized Root Mean Square Error of Approximation; Ref = Reference Model; $\Delta S\chi^2$ = Satorra-Bentler Scaled chi-square difference test; Δdf = change in degrees of freedom; ΔCFI = change in CFI; ΔRMSEA = change in RMSEA;
[a] $p<.06$. * $p<.05$. ** $p < .01$. *** $p \leq .001$

Table 3

Growth Parameters for the Final Selected Models

Models	Intercept Mean [95%CI]	Intercept Variance	Slope 1 Mean [95%CI]	Slope 1 Variance	Slope 2 Mean [95%CI]	Slope 2 Variance	Correlation Intercept /Slope 1	Correlation Intercept /Slope 2
Autistic Symptoms	31.189*** [30.199, 32.179]	45.616***	-1.877*** [-2.462, -1.291]	0.131	-	-	.625	-
General Adaptive Composite	64.891*** [62.985, 66.796]	203.603***	6.192*** [4.657, 7.728]	29.861	-0.726 [-3.625, 2.173]	19.144	.168	-.427
Conceptual Domain	68.480*** [66.531, 70.428]	196.284***	6.960*** [5.469, 8.451]	25.776	-1.401 [-4.160, 1.358]	36.127	.192	-.605**
Social Domain	70.580*** [68.449, 72.710]	229.188***	5.979*** [4.302, 7.656]	2.374	0.240 [-2.837, 3.316]	19.652	.374	-.624
Practical Domain	65.499*** [63.675, 67.322]	178.176***	2.985*** [1.574, 4.395]	35.070	-0.079 [-3.334, 3.175]	87.492**	.066	.018

Note. CI = Confidence intervals
* p<.05. ** p < .01. ***p ≤.001

Table 4

Predictors of the Growth Parameters for the Final Selected Models

	Intercept		Slope 1		Slope 2	
	Estimate	[95%CI]	Estimate	[95%CI]	Estimate	[95%CI]
Autistic Symptoms						
GACT1	-.584***	[-.728, -.441]	-.042	[-.835, .750]	-	
Age T1	-.199***	[-.331, -.087]	-.263	[-.975, .449]	-	
Income	-.055	[-.176, .065]	.247	[-.678, 1.172]	-	
Intensity	.082	[-.052, .217]	-.716[a]	[-1.457, .025]	-	
.PIQ	-.101	[-.258, .055]	-.841	[-1.182, .130]	-	
GLC	-.102	[-.383, .179]	1.358[a]	[-.051, 2.768]	-	
VIQ	.035	[-.215, .285]	-1.069	[-2.564, .426]	-	
General Adaptive Composite						
AST1	-.499***	[-.600, -.398]	-.366**	[-.638, -.095]	.136	[-.466, .738]
Age T1	-.028	[-.114, 0.57]	.052	[-.152, .256]	-.431**	[-.759, -.104]
Income	.084	[-.012, .179]	- .137	[-.336, .061]	-.105	[-.508, .299]
Intensity	-.085[a]	[-.172, .003]	.139	[-.076, .355]	.068	[-.351, .486]
PIQ	.105	[-.040, .250]	-.008	[-.318, .301]	.575[a]	[-.015, 1.165]
GLC	.082	[-.190, .354]	.285	[-.157, .728]	-.672	[-1.544, .200]
VIQ	.148	[-.085, .382]	.044	[-.411, .499]	-.672	[-.490, 1.077]
Conceptual Domain						
AST1	-.381***	[-.494, -.268]	-.288*	[-.569, -.006]	.070	[-.600, .740]
Age T1	-.005	[-.092, .083]	-.008	[-.248, .233]	-.421**	[-.730, -.112]
Income	.118*	[.022, .215]	-.088	[-.308, .132]	-.180	[-.558, .199]
Intensity	-.065	[-.170, .040]	.193	[-.050, .436]	-.023	[-.447, .401]
PIQ	.176*	[.036, .317]	-.002	[-.324, .321]	.207	[-.403, .816]
GLC	.319*	[.020, .618]	.085	[-.387, .556]	-.465	[-1.332, .392]
VIQ	.008	[-.241, .258]	.266	[-.231, .763]	.184	[-.543, .912]
Social Domain						
AST1	-.603***	[-.718, -.489]	-.276	[-.865, .314]	.008	[-.695, .711]
Age T1	-.068	[-.166, .030]	.155	[-.255, .565]	-.205	[-.665, .256]
Income	.007	[-.104, .118]	.323	[-.903, .257]	.073	[-.410, .557]
Intensity	-.084	[-.191, .023]	.302	[-.237, .841]	.174	[-.338, .687]
PIQ	.068	[-.093, .229]	.042	[-.569, .654]	.475	[-.295, 1.244]
GLC	.090	[-.170, .350]	.396	[-.625, 1.418]	-1.034*	[-2.063, -.005]
VIQ	.112	[-.135, .359]	.056	[-.809, .920]	.346	[-.610, 1.301]
Practical Domain						
AST1	-.492***	[-.607,-.377]	-.400*	[-.758, -.043]	.168	[-.365, .691]
Age T1	-.011	[-.116, .093]	-.017	[-.260, .227]	-.385*	[-.681, -.089]
Income	.035	[-.071, .140]	-.048	[-.271, .176]	-.086	[-.426, .255]
Intensity	-.057	[-.159, .045]	.039	[-.206, .284]	.001	[-.378, .380]
PIQ	.089	[-.066, .244]	-.113	[-.465, .238]	.557*	[.022, 1.092]
GLC	.059	[-.218, .336]	.364	[-.144, .871]	-.239	[-1.109, .630]
VIQ	.188	[-.054, .430]	-.152	[-.688, .384]	.129	[-.676, .935]

Note. The standardized estimates are reported. GAC = General Adaptive Composite; AS = Autistic Symptoms; PIQ = Performance Intellectual Quotient; VIQ = Verbal Intellectual Quotient; GLC = Global Language Composite; T1 = Time 1

[a] $p<.06$. * $p<.05$. ** $p < .01$. *** $p \leq .001$.

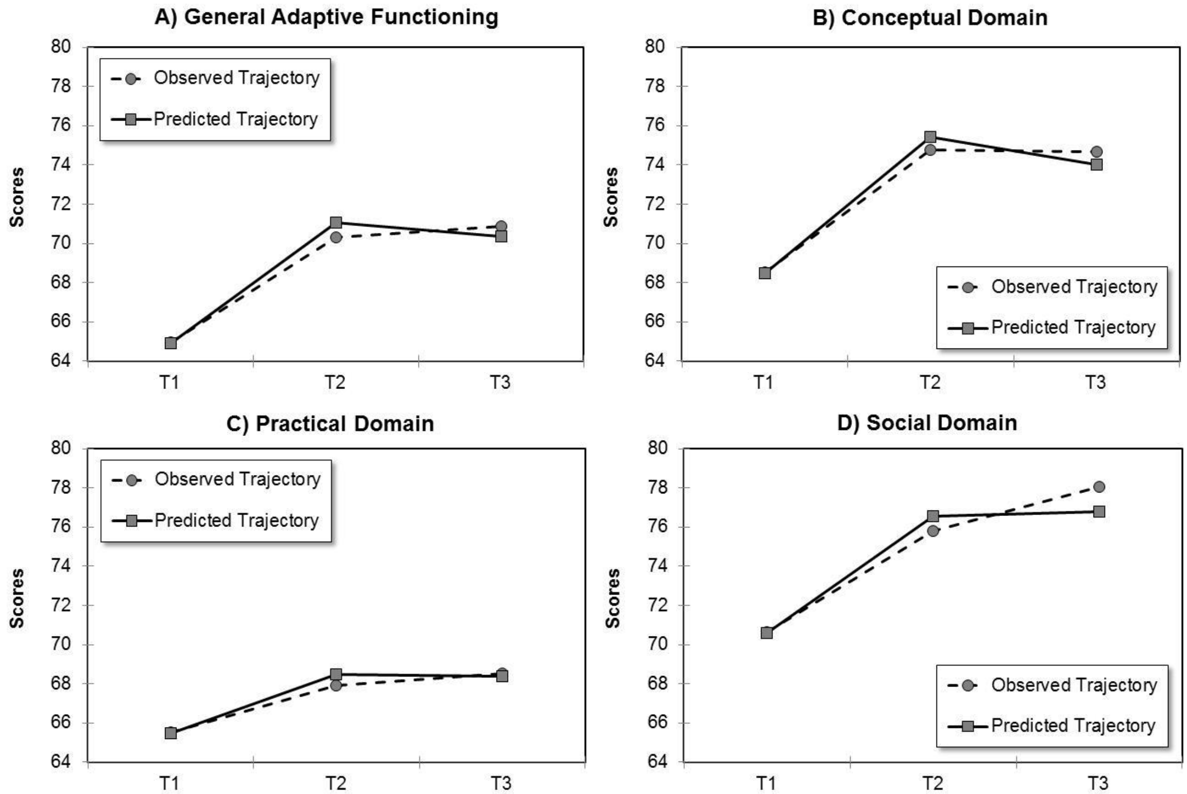

Figure 1. Mean Scores for the Observed and Estimated Latent Trajectories