The School of Mathematics

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Charting the Impact of Bilingualism on Language and Cognitive Development in Autistic Children

by

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Own Work Declaration

I confirm that the work contained in this report is my own except where otherwise indicated.

Acknowledgement

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Word Count

5000 words(including the executive summary, main text and references; excluding appendices).

Executive summary

Background

Autism is a neurodevelopmental condition associated with intellectual disability and language delay is the most common symptom. From the very limited literature, bilingual exposure is unlikely to lead to poorer development of language in autistic children and could provide an advantage in social and communicative domains but the evidence is really weak. Parents are still worried about whether bilingualism may cause confusion and hinder children's linguistic development.

Research Question

This report aims to explore whether bilingualism offer an advantage for autistic children and explore how bilingualism might influence autistic children in language, social cognitive and executive function domains.

Data

In 'Raw Data.xls', there are 89 participants aged 5-13 who are being raised in a bilingual environment including 58 non-autistic childrenNeurotypical childrenand 31 autistic children. The 43 variables can be divided into four parts: One basic part can review participants bilingualism exposure level; another part is related to children's IQ and Language ability; a series of variables can show children's social cognition ability and some variables illustrate the degree of executive function.

Work

Firstly, I group the data set into autistic children and non-autistic children (Neurotypical children) according to diagnosis and I impute the missing data with mice package in R. Besides, I explore the correlation relationship between bilingualism and children's intelligence, language ability, social cognitive ability, executive ability and construct latent variables. Finally, based on confirmatory factor analysis, I explain the difference in the impact of bilingual environment on children with autism and non-autistic children based on structural equation models.

Findings

Bilingual exposure can enhance autistic children's language ability through positive influence on intelligence. Besides, it will also promote their interests in social interaction. If the time for bilingual input of autistic children increases by 1 point, the dwell time to interacting figures increases by 5.27 ms. Early exposure to bilingual autistic children is stronger in inhibit, self control and task than later exposure children. Finally, bilingualism has a stronger positive effect on autistic children compared with non-autistic children especially in the aspects of behavioural regulation.

Contents

1 Introduction

Autism Spectrum Disorder (hereafter) ASD is among the most common neurodevelopmental disorders, affecting one in 68 children (Wingate et al., 2014) which is characterized by challenges in social communication and interaction and by restricted, repetitive behaviors and interests (American Psychiatric Association, 2013). These kinds of behaviors or symptoms must be present in early childhood and autistic children could have lifelong difficulties in social and communicative domains.

Nowadays, many studies have shown that compared with monolingual children, early bilingual education has a positive effect on children's language ability, cognitive control, social interaction, etc. However, there is a scarcity of research investigating how bilingualism might interact with autism. From the very limited literature, we can only find that bilingual exposure is unlikely to lead to poorer development of language in autistic children. Besides, it could provide an advantage in social and communicative domains but the evidence is really weak.

Parents with an autistic child or lower verbal ability feel difficult to make language exposure choices for kids and expressed concerns that a bilingual environment would cause confusion and exacerbate language delays. So this report aims to contribute to the question by comparing the performance in various fields between autistic children and non-autistic children grew up in bilingual environment. We hope to better comprehend how bilingualism and autism might interact.

We analyze a sample of 89 children aged 5-13, with an average age of 8.67 years. Our goal is to compare the development in language, social cognition and executive function fields between 38 autistic children and 51 non-autistic children by using exploratory data analysis and structural equation models. We hope to better understand which of these factors should be influencing parents' decision.

2 Test Classification & Data Processing

In 'Raw Data.xls', there are 89 participants aged 5-13 who are being raised in a bilingual environment including 58 non-autistic childrenNeurotypical childrenand 31 autistic children. The 43 variables can be divided into four parts: bilingual exposure, IQ, language, social cognition and Executive function.According to the classification of variables, I adapt different methods to identify and deal with missing data and outliers.

1. Bilingual Exposure
   There are six variables including the amount of time spent speaking of hearing English and non English which are provided by parents and the total score of bilingual input and output. However, there are some autistic children who don't talk or have any language skills so it's all about how much they are hearing another language. I use total input to represent bilingual exposure in analysis.

2. IQ
   IQ is the sum of all raw scores for the 2 WASI tests. Participants numbered 1005, 1008, 1040 are missing IQ test values. I find that missing is not completely at random. Specifically, MAR implies that those subjects with missing values in IQ have extreme values for vocabulary. The minimum IQ is in total sample is 10, So I impute 9 as their IQ result.

3. Language: Vocabulary & Processing Speed
   There are two variables that can reflect language ability: vocabulary and language processing speed. In raw BPVS scores, I find that participants No. 1029 and No. 1032 are 166 and 162 respectively, which exceeded the valid range of 0-155. According to a comprehensive analysis of their diagnosis results, age, gender, and vocabulary, I replace them with 155.

I find language Processing Speed score has high correlation coefficients with vocabulary, age, and IQ score so I select individuals in the same group with similar age, vocabulary, IQ score and calculate the mean to impute each missing data.

4. Social Cognition
   The Theory of Mind Inventory (TOMI), Theory of Mind Task Battery (TOMTB) and novel eye tracking tasks(Figure Task) can reflect children's social cognition conditions including a total of 9 variables. First, I use 'VIM' package in R to draw the pattern of missing data.

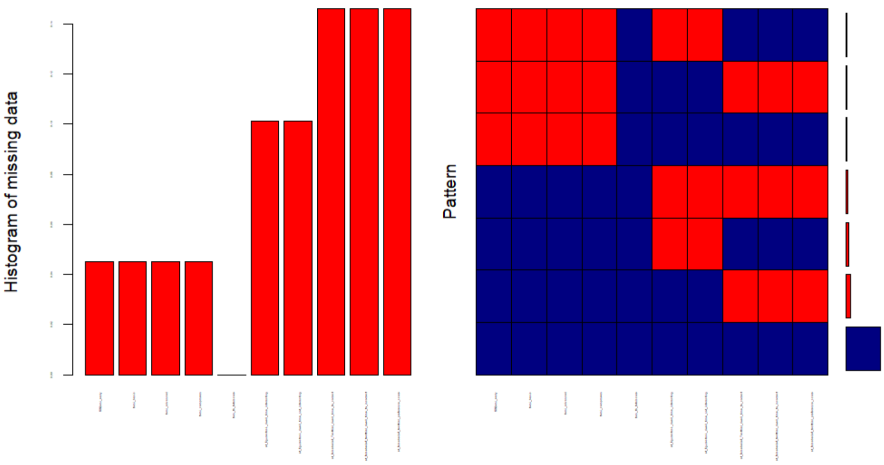

Figure 1: Missingness in Social Cognition Variables

In Figure 1, we can see that the missing rate is low in TOMI test, there are 3 missing values in the autistic group and only 1 missing value in the non-autistic group and the missing values belongs to pairwise missing. So I choose individuals with similar characteristics (correlation coefficient with other variables to define 'similar') and calculate the mean to impute in each missing data. In the Figure Task, I also impute missing data with values from similar individuals.

5. Executive Function
   Executive Function is measured by three tests, The Behavior Rating Inventory of Executive Function (BRIEF), The Flanker Task and The Psychomotor Vigilence Task (PVT) with 9, 4 and 4 variables respectively. First, I use 'VIM' package in R to draw the pattern of missing data.

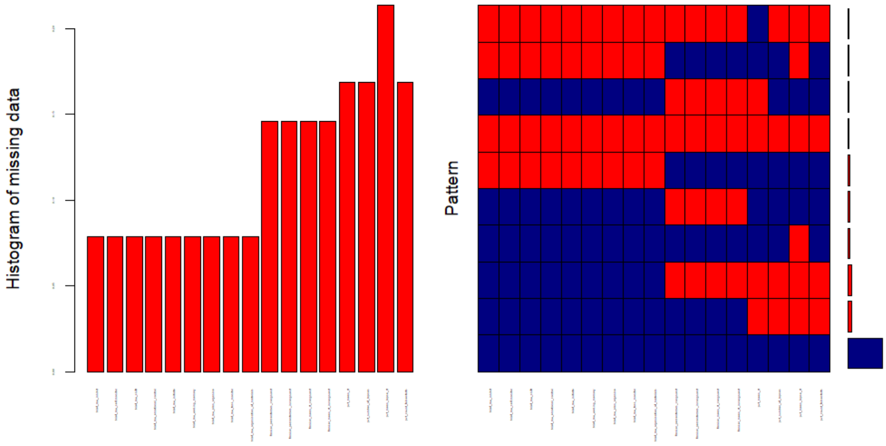

Figure 2: Missingness in Executive Function Variables

From Figure 2, we can find that missing belongs to the whole group of deletions in BRIEF so I use multiple regression models to impute the missing data. Besides, Flanker and PVT test are computerised tests while the missing rates are relatively high. Through the observation of missing children's score in other tests, I think the missing values may be related to the participants' own factors.
First, I directly delete the data values of No. 1019, No. 1040, and No. 1051, all of which belong to the autistic group since all their executive function test results are missing and they are likely to have extreme values. Then there is only 1 participant in the autistic group are missing (no.1029), and only 3 of 51 in non-autistic group are missing so I use mice and acquire 5 complete data set. I choose the third data set to impute the missing values in BRIEF test. Besides, according to the correlation analysis, I find that the PVT result has a high correlation with the Flanker Task result and all coefficients are greater than 0.5. I fit regression models for each variable in a loop, adjust the model according to the significance of the regression coefficient and then use mice package to generate 5 complete data sets, I select the third data set to impute the missing values.

3 Descriptive & Exploratory Data Analysis

3.1 Descriptive Statistical Analysis

I first group the data set into two groups according to diagnosis, 38 autistic children and 51 non-autistic children (Neurotypical children). Among 51 non-autistic children, the SCQ ranged from 0-10, with an average value of 2.7, indicating that the autistic traits of the non-autistic children in the sample are not obvious, so the two groups can be compared for analysis. Besides, the sex ratio is 52:37 which is roughly the same of two groups.

1. Bilingual Exposure Level
   I analyse statistics of bilingual exposure variables and perform an independent sample T test for the children in the autistic group and non-autistic children. The test results are shown in the following table.

mean± std.	autistic	non-autistic	t	p-value
Hear non-English	34.4±21.7	42.3±22.1	-1.69	0.09
Hear English	64.6±21.5	57.5±22.5	1.50	0.14
Speak non-English	25.1±24.6	33.8±25.3	-1.63	0.11
Speak English	74.8±24.6	66.0±25.7	1.63	0.11
Overall Input	54.7±27.8	59.1±23.2	-0.81	0.42
Overall Output	38.8±33.5	46.3±28.7	-1.12	0.26

$*p < 0.05, **p < 0.01$

Table 1: Bilingual Exposure Description

Table 1 shows that there is no difference of bilingual exposed level between autistic group and non-autistic group since all p-values are greater than 0.05. People used to think that the output ability of autistic children should be lower than that of normal children. However, the T-test results indicates that under certain conditions and similar bilingual exposure environment, there is no difference between the bilingual ability of autistic children and non-autistic children. Bilingual exposure can also result in bilingual ability in autistic children regardless of their own expressive language level. Besides, the average time of hearing English and non-English in the autistic group are higher than that of the non-autistic group so the overall input of autistic group are higher than that of the non-autistic group. In contrast, autistic children speak less English or non-English than non-autistic children. Some children are not verbal so I consider Overall input a better overall representation of exposure.
In addition, I classified the autistic children into 3 groups through cluster analysis to explore whether there is a difference between different dose level of bilingual exposure in various aspects.

mean ± std	Low(31)	Medium(24)	High(31)	F	p-value
Bilingual exposure	30.39±10.64	62.50±15.73	80.03±13.10	114.058	0.000**

$*p < 0.05, **p < 0.01$

Table 2: Dose of Bilingual Exposure Groups

In Table 2, the proportions of the three groups of low, medium and high are 36.05%, 27.91% and 36.05% respectively. On the whole, the distribution of autistic children is relatively even, and the clustering effect is ideal.

2. Time of Bilingual Exposure
The average age at which all children acquire a second foreign language is 0.56 (years old) which shows that children have been exposed to a bilingual environment from a very young age.

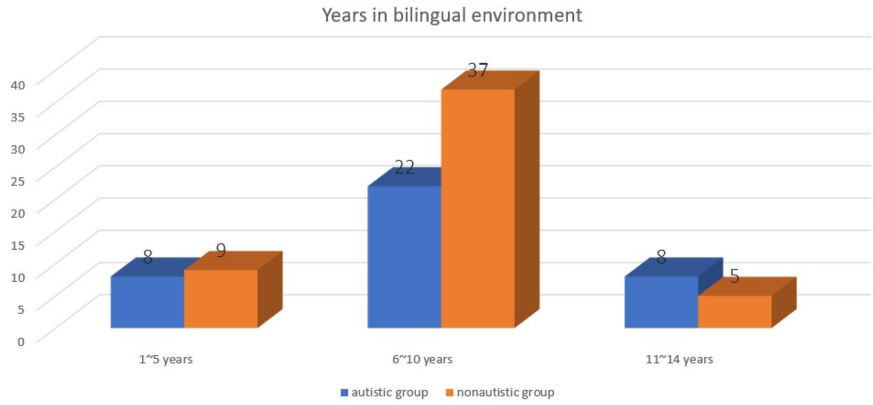

Figure 3: Years in Bilingual Environment

Figure 3 shows that the time distributions of children's exposure to a bilingual environment in two groups are similar. Most children have grown up in a bilingual environment for 6 to 10 years and 15% of children have been exposed to a bilingual environment for more than 11 years. It shows that the children in the sample have been exposed to two languages for a long time. There is no difference in age of child acquiring second language between two groups.

3. Bilingual Place

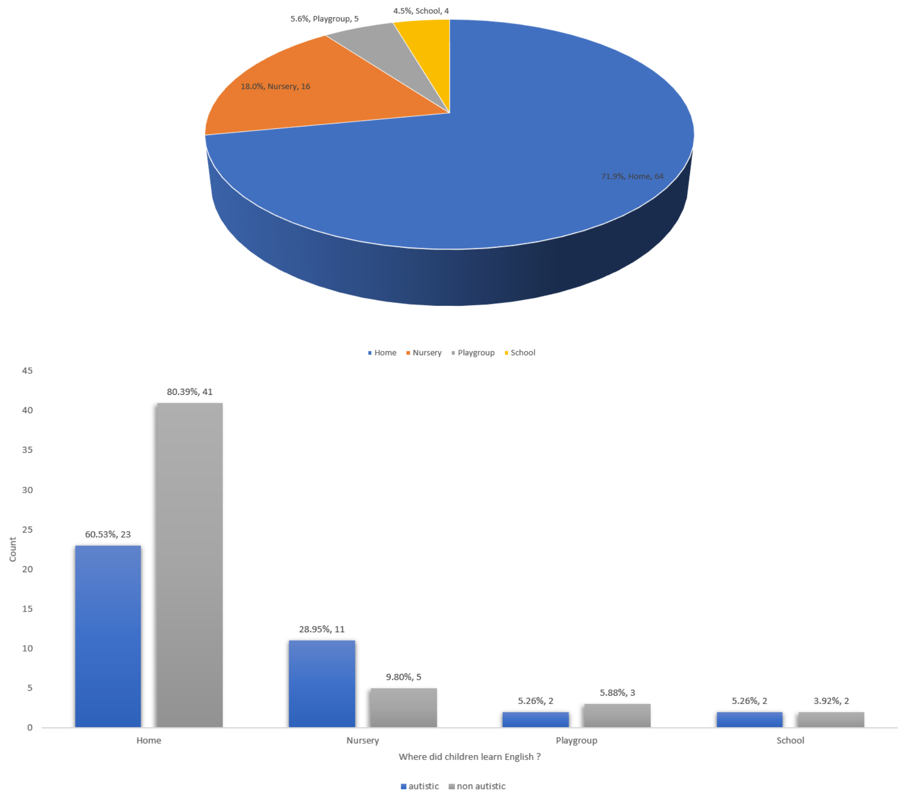

Figure 4: Where did children learn English ?

In Figure 4, there are four places where children learn English and in both two groups, most children learn English at home. Autistic children have a higher proportion to learn English in nursery.

3.2 Exploratory Data Analysis

According to the type of information reflected by tests, I compare and analyze the performance of children in the autistic group and children in the non-autistic group in four areas: IQ, language ability, social cognition and executive function. First, I perform an independent sample T test on two groups. All the results are shown in the table below.

mean±std	autistic	non-autistic	t	p-value
age-acquisition	0.76±1.36	0.41±1.04	1.38	0.17
IQ	31.1±15.5	36.5±10.5	-2.13	0.037
vocabulary	98.1±40.4	109.9±22.8	1.62	0.11
speed	2787.6±171.6	2756.6±144.8	0.92	0.36
t-early	15.2±2.4	18.6±1.2	-8.77	0.00**
t-basic	14.0±3.5	18.8±1.3	-7.90	0.00**
t-advanced	9.0±4.1	16.6±2.7	-10.03	0.00**
t-comp	12.4±2.9	17.9±1.7	-10.41	0.00**
tom_total	10.9±3.0	12.9±1.6	-3.54	0.00**
interact	1029.9±337.4	1209.7±442/2	-2.09	0.039*
no-interact	933.4±260.0	1039.7±363.6	-1.53	0.13
correct	3467.6±1656.9	4416.5±1159.6	-3.02	0.004**
incorrect	3507.5±1637.6	3933.5±1185.6	-1.42	0.16
preference	322.4±1623.0	482.4±1724.3	-0.44	0.66
inhibit	16.9±4.2	11.7±4.2	5.86	0.00**
Self-monitor	9.2±2.3	6.9±6.3	2.20	0.03*
shift	17.8±4.4	10.4±2.3	10.38	0.00**
Emotion-control	16.9±5.1	11.1±3.2	6.18	0.00**
Initiate	11.0±3.0	6.5±1.6	8.32	0.00**
Working memory	16.9±4.0	10.4±2.5	8.00	0.00**
Plan-organisation	16.9±3.9	11.4±2.6	7.55	0.00**
Task-monitor	11.2±3.2	7.3±2.03	6.63	0.00**
Material-organisation	11.4±2.9	9.2±2.59	3.89	0.00**
Per-conurgent	21.1±28.1	7.4±11.9	2.73	0.01*
Per-inconurgent	22.2±29.4	12.2±17.1	1.82	0.07
Mean-conurgent	1022.0±435.7	972.5±306.0	0.62	0.54
Mean-inconurgent	1073.6±436.6	1094.8±424.6	-0.22	0.82
Pvt-mean	1398.7±1721.6	599.8±289.3	3.3	0.00**
Pvt-no	17.0±13.1	16.9±12.4	0.04	0.97
Pvt-lapse	858.5±1246.5	380.0±506.1	2.12	0.04*
Pvt-fault starts	11.86±18.2	11.7±14.6	0.15	0.88

$*p < 0.05, **p < 0.01$

Table 3: Autistic vs Non-autistic

In Table 3, if p-value is smaller than 0.05, then there is a difference in the performance of autistic children and non-autistic children in this aspect otherwise, there is no difference between the two groups. As a result, the two groups do not show significant difference in a total of 12 variables of different tests such as vocabularylanguage processing speeddwell time to interacting or not interacting figures and so on. This means that the performance of autistic and non-autistic children in these aspects is almost similar and there is no evidence that bilingual environment will hinder the development of autistic children in these aspects.

1. IQ & Language

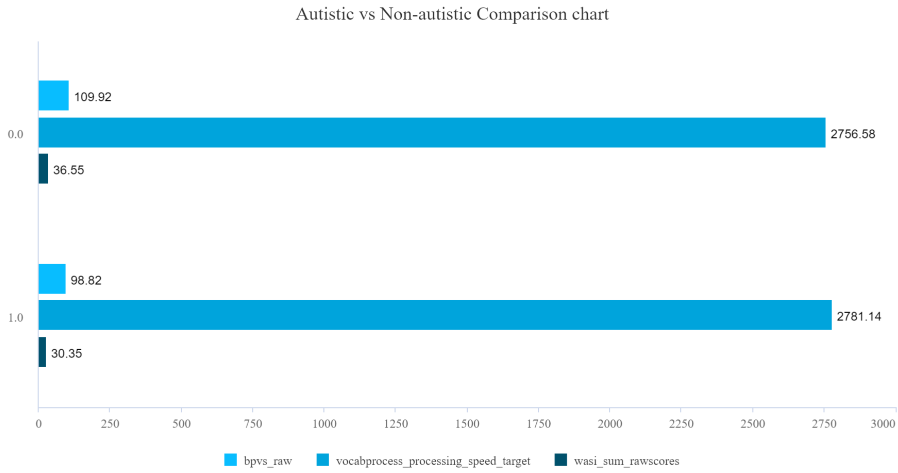

Figure 5: Comparison Chart in IQ and Language Tests

According to the T-test results, there is only a difference in IQ between autistic and non-autistic children, which is also reflected in the Figure 5. At the same time, the two groups show similar level of vocabulary and language processing speed. Non-autistic children are slightly better than autistic children in vocabulary and language processing speed, but there is no significant difference, indicating a bilingual environment will not hinder the development of language skills of autistic children.

2. Social Cognition
   -TOMI and TOMTB

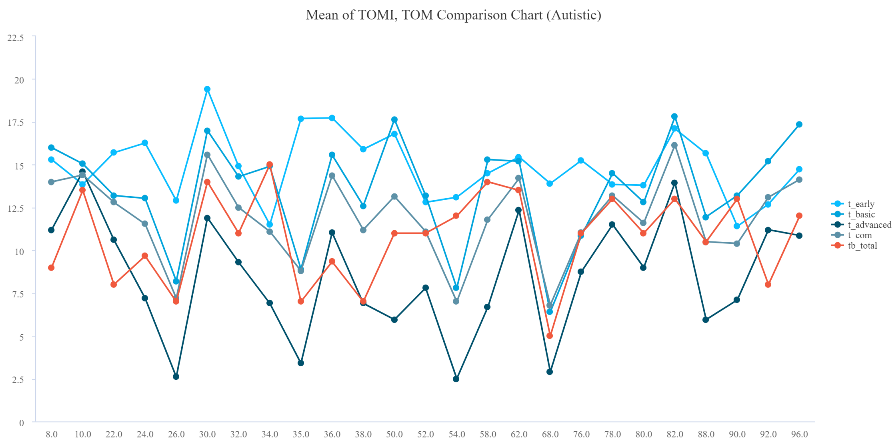

Figure 6: Comparison Chart in TOMI and TOMTB Tests

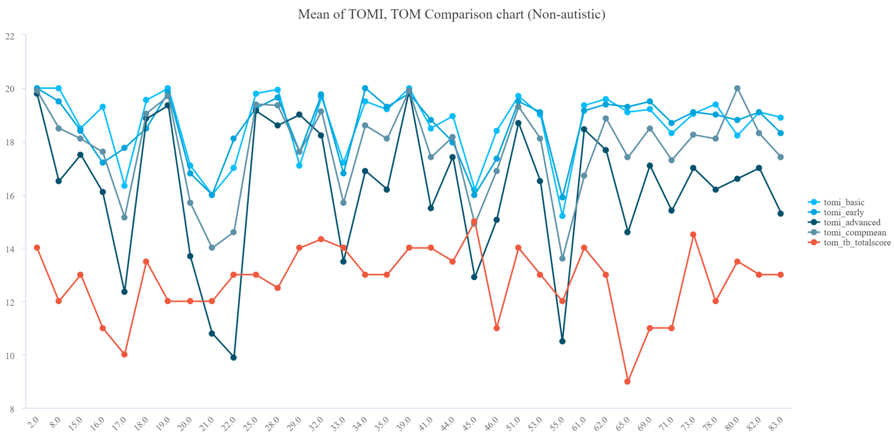

Figure 7: Comparison Chart in TOMI and TOMTB Tests

Figure 6 and 7 compares the performance of autistic children and non-autistic children in the Theory of Mind Inventory(TOMI) and Theory of Mind Task Battery(TOM) tests. There are obvious differences in the performance of the two groups. The early, basic and advanced social skills of non-autistic children are all better than those of autistic children, and they have better understanding since higher score means better understanding.

-Eye-tracking Tasks

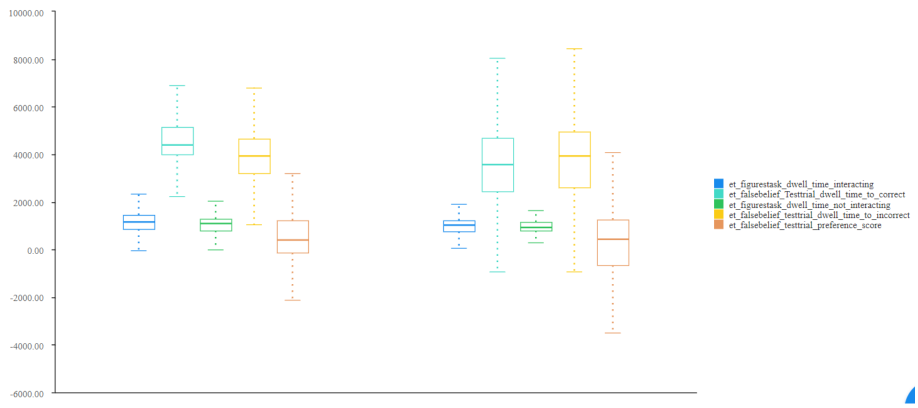

Figure 8: Comparison Chart in Eye-tracking Tests

Figure 8 shows the performance of the autistic group and the non-autistic group in Eye-tracking Tasks. The box plot shows that the results are consistent with that of independent sample T test. On the total looking time to correct picture (ms), there is a significant difference between children and non-autistic children, since Children looking longer at the correct picture are seen to answer the question correctly, the performance of autistic children is weaker than that of non-autistic children. In other respects, the two groups performed similarly.
Besides, I also notice that autistic children and non-autistic children almost spent the same time observing interacting human figures while focusing on the figures who look like they're having a conversation, rather than the ones people are back to back can be indicative of the fact that, children are more interested in social interaction. So a bilingual environment will promote autistic children's interest in social interaction to a certain extent.

3. Executive Function

-The Behavior Rating Inventory of Executive Function (BRIEF)
Executive functioning is broken down into clinical scales divided by Behavioral Regulation (Inhibit, shift and emotional control) and Meta cognition (Initiate, Working Memory, Plan or Organize, Organization of Materials, Monitor). The performance of the autistic group and the non-autistic group of 9 sub-scales is shown in Figure 9 as follows.

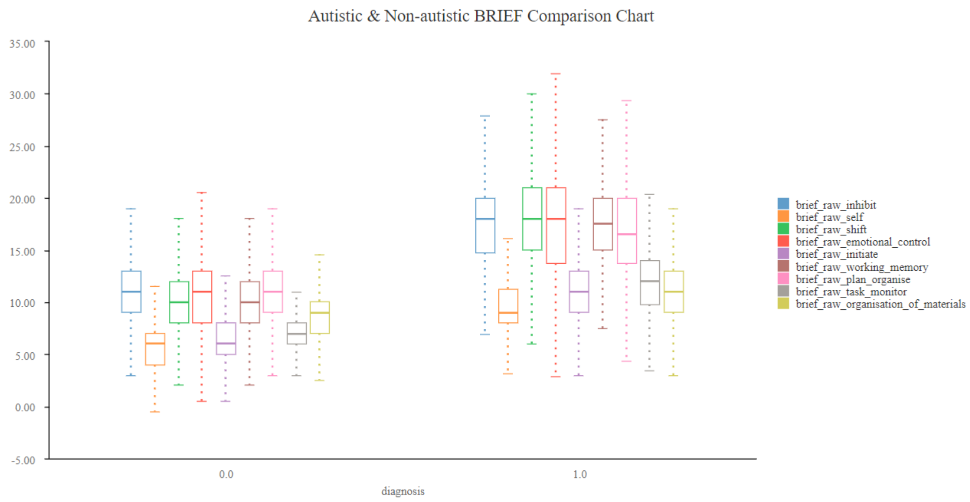

Figure 9: Comparison Chart in BRIEF

In BRIEF tests, the autistic group and the non-autistic group shows significant differences in 9 aspects. From Figure 9, it can be found that the range of autistic children is much larger and each item score is higher than that of the non-autistic group.

-The Flanker Test

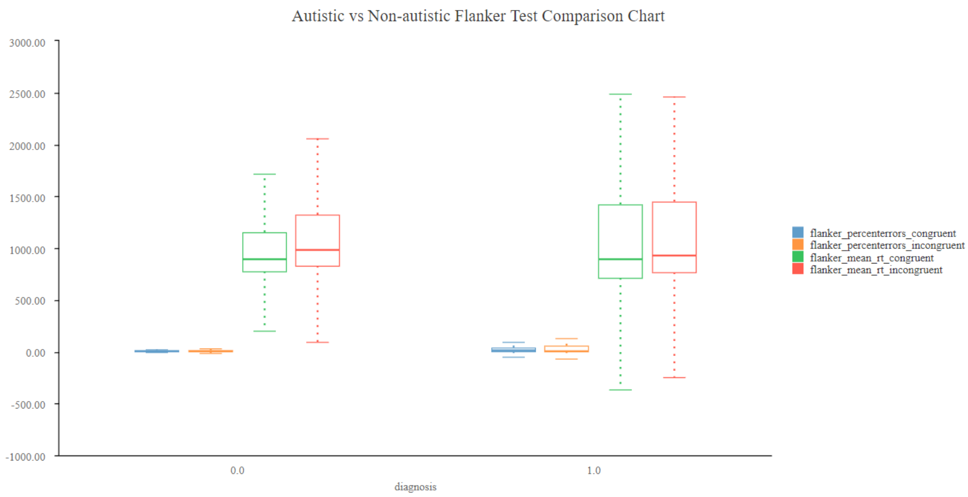

Figure 10: Comparison Chart in the Flanker Task

The Flanker task is used as a measure of inhibition. The test results show that the error rate of autistic children in all consistent trials is higher than that of non-autistic children, and the average error rate in discordant tests is higher than that of non-autistic children. There is no significant difference. Otherwise, the average reaction time of the two groups of children was similar. Therefore, bilingual contact may have an impact on the inhibition of autistic children, but it will not reduce the speed of their correct response.

-The Psycho motor Vigilance Task (PVT)
The Psycho motor Vigilance Task is a computerized task to check children's sustained attention by responding to the target stimulus on the screen. The PVT results of two groups are in Figure 10 and Figure 11. Autistic children have less sustained attention than non-autistic children, but the false starts and number of lapses of autistic children are similar to those of non-autistic children.

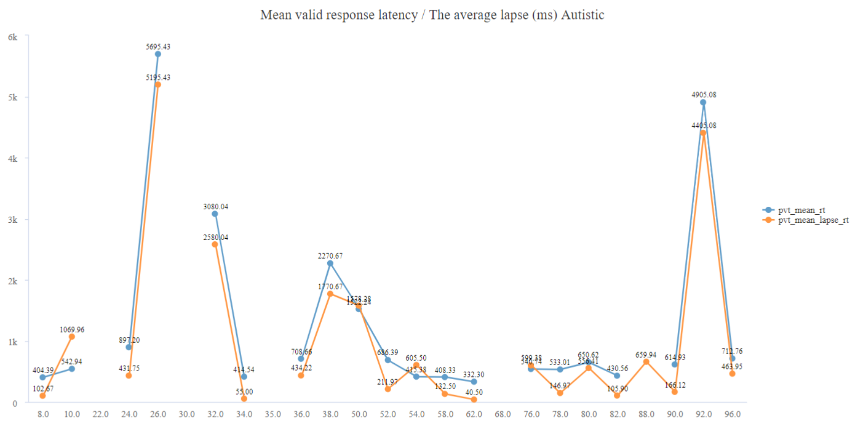

Figure 11: Comparison Chart in Mean valid response latency / The average lapse (ms)

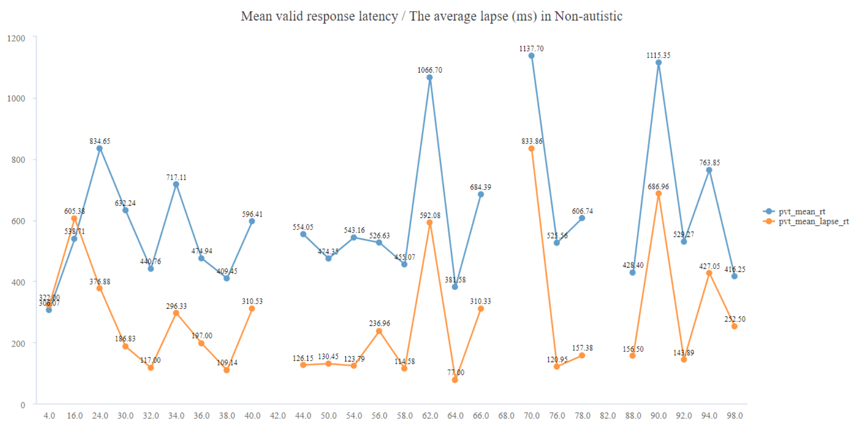

Figure 12: Comparison Chart in Mean valid response latency / The average lapse (ms)

It can be seen from Figure 11 and 12 that the average effective response time of autistic children to the target is similar to that of the non-autistic children groupthe average lapse in autistic group are smaller, so there is no evidence that bilingual exposure will reduce the effective response speed of autistic children to goals. But the response of the autistic group to the target has a larger extreme value, while the overall response speed of the non-autistic children is more average.
However, with the increase of bilingual exposure, the effective response time of autistic children to the target tends to stabilize at a lower level, so I think bilingual exposure can helps improve the response speed of autistic children to goals.

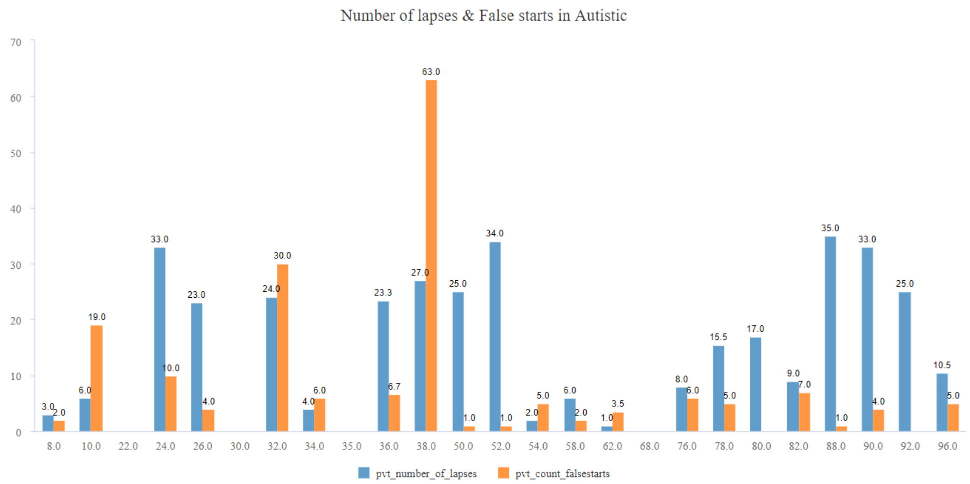

Figure 13: Comparison Chart in Number of lapses False starts

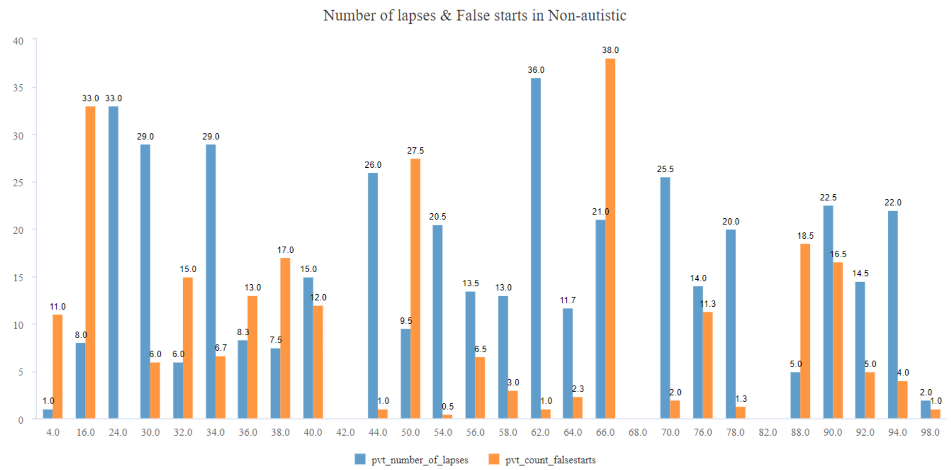

Figure 14: Comparison Chart in Number of lapses False starts

According to the independent sample T test results, there is no difference in the total number of lapses and false starts between autistic children and non-autistic children as shown in Figure 13 and 14. Besides, among children with autism, as the level of bilingual exposure increases, the number of false starts is significantly reduced. According to the cluster analysis, autistic children with low, medium and high bilingual exposure levels have significant differences in false starts numbers.

Overall, I use total input to represent bilingual exposure and try to construct structural equation models in Language, social cognition and executive function fields.

4 Bilingual Exposure Influence on Language

4.1 Correlation Analysis

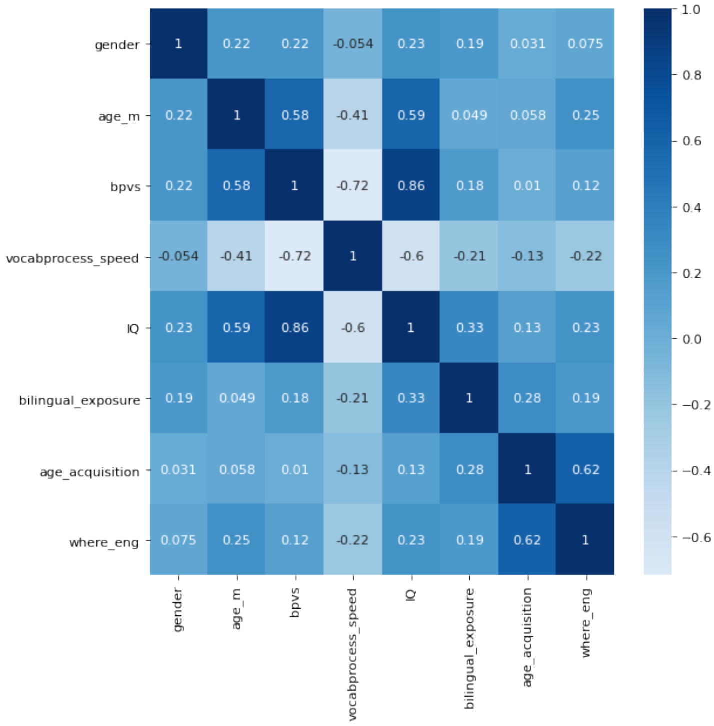

Figure 15: Correlation Analysis in Autistic Group

Figure 15 shows that the correlation in autistic group between bilingual exposure and IQ is significant, the correlation coefficient value is 0.329, indicating that there is a positive correlation between bilingual exposure and IQ for autistic children. However, the correlation coefficients between bilingual exposure and gender, age, vocabulary, processing speed, acquisition age, where children learn English are not significant and coefficients are close to 0, indicating that there is no correlation between bilingual exposure and the 6 items.
Besides, I find that IQ also has significant positive influence on vocabulary and language processing speed. Therefore, I construct structural equation models in autistic group.

In non-autistic group, there is no correlation between bilingual exposure and gender, age, vocabulary, SCQ, vocabulary process speed, IQ, acquisition age, and where children learn English. The correlation coefficient values are 0.095, 0.033, -0.004, -0.050, -0.174, 0.075, -0.052, 0.096 respectively, all are close to 0 and p-values are greater than 0.05. So I only build models for autistic children.

4.2 Language Structural Equation Model

Based on the correlation analysis, the structural equation model path analysis diagram is as follows.

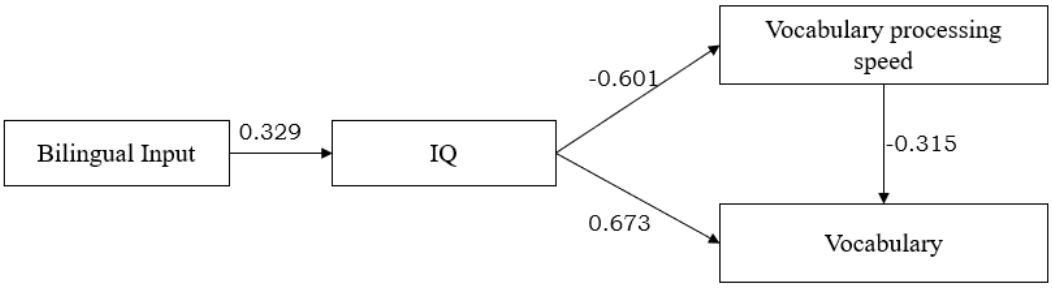

Figure 16: Language Structural Equation Model Path Diagram

X	→	Y	SE	z	p-value	st path coef.
Bilingual	→	IQ	0.085	2.15	0.032**	0.329
IQ	→	Process speed	1.439	-4.638	0.00**	-0.601
IQ	→	Factor	0.233	7.548	0.00**	0.673
Process speed	→	Vocabulary	0.021	-3.533	0.00**	-0.315

$*p < 0.05, **p < 0.01$

Table 4: Language Structural Equation Model Regression Coefficient

In Table 4 , the four paths in the model are all significant, the analysis shows that for every additional point in the bilingual exposure score, the IQ test of autistic children will increase by 0.33 points, so the time for autistic children take to make the first fixation (or look) to the correct picture is shortened by $0.33 * 0.601 = 0.198ms$ and the language processing speed is increased. At the same time, the English vocabulary score obtained by autistic children in BPVS will also increase by $0.33 * 0.674 + 0.601 * 0.315 = 0.412$. So I think Bilingual exposure can improve language ability through positive influence on intelligence.(Both paths pass the mediation test of Bootstrap sampling.)

χ^2	df	p	χ^2/df	GFI	NFI	NNFI	TLI
2.409	2	0.3	1.204	0.9	0.972	0.985	0.985

Table 5: Language Structural Equation Model Fitting Index

In Table 5, we can see that χ^2/df is smaller than 3, GFI is smaller than 0.9; RMSEA is smaller than 0.1; RMR is smaller than 0.05; CFI, NFI, NNFI and TLI are all greater than 0.9 so the language structural equation model fits well.

5 Bilingual Exposure Influence on Social Cognition

5.1 Correlation Analysis

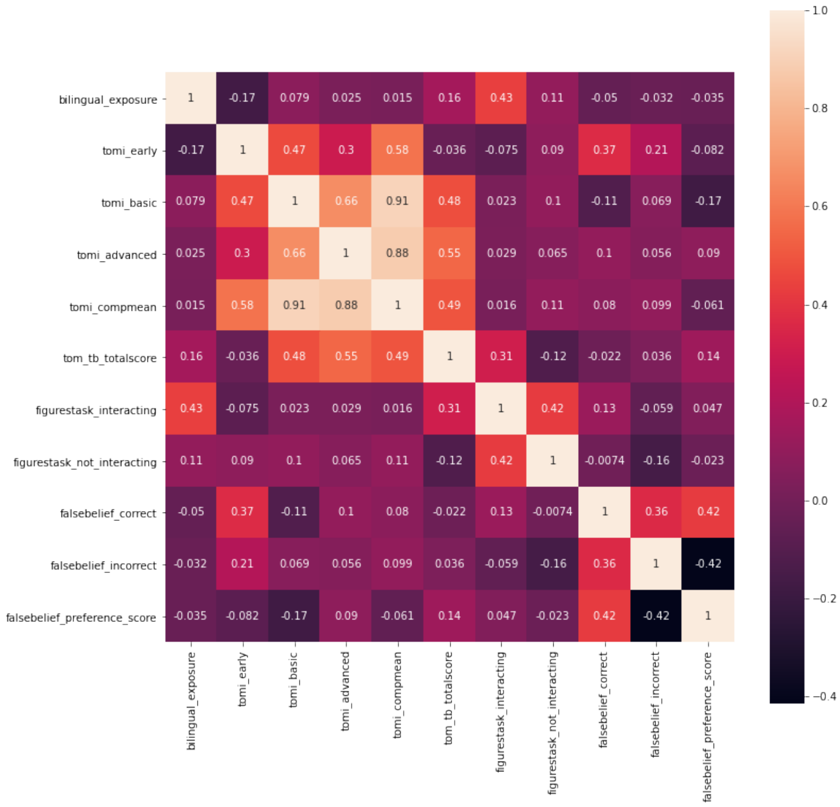

Figure 17: Correlation Analysis in Autistic Group

In Figure 17, it can be seen from the significant test analysis of the correlation coefficients that a total of five variables in TOMI and TOMB have no correlation with bilingual exposure, TOMB total score has significant positive correlations with early, advanced and composite mean score of TOMI, the correlation coefficients are 0.479, 0.549, 0.494, respectively. Besides, TOMI Composite Mean is a composite score of Early Basic and Advanced raw scores. However IQ has positive correlations with some of variables so I considered introducing IQ to build structural equation models. (I also try factor analysis or principal component analysis on 5 variables, and the KMO is 0.370<0.5, the effect is not satisfactory.)

In addition, Figure 17 shows that Bilingual exposure has a significant positive correlation with the time of interacting figures which suggests bilingual exposure could improve the social interaction tendency of autistic children. At the same time, the total looking time to interacting and not human figures are significantly related, therefore I can also set up structural Equation Models.

5.2 Social Cognition Structural Equation Model

1. Social Cognition Model in TOMI & TOMB
   Based on the correlation analysis, the structural equation model path analysis diagram is as follows.

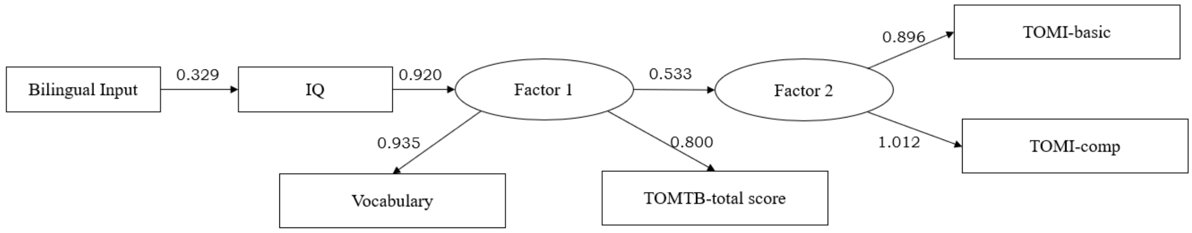

Figure 18: Social Cognitive Structural Equation Model Path Diagram

X	→	Y	SE	z	p-value	st path coef.
Bilingual	→	IQ	0.085	2.15	0.032*	0.329
IQ	→	Factor 1	0.021	6.757	0.00**	0.92
Factor 1	→	Factor 2	0.234	2.997	0.003**	0.533

$*p < 0.05, **p < 0.01$

Table 6: Social Cognitive Structural Equation Model Regression Coefficient

In Table 6, I find that for every additional point in the bilingual exposure score, the IQ test of autistic children will increase by 0.33 points and we can infer TOMB total score could be slightly higher than before (approximately 0.24). Besides, Latent variable would also increase, as a result, TOMI-basic score and TOMI-comp would increase 0.14 and 0.16 respectively. Although the influence of bilingual exposure on autistic children through latent variables as intermediate variable is weak, it can still show that bilingual exposure has a positive effect on TOMI and TOMB results.

χ^2	df	p	χ^2/df	GFI	NFI	NNFI	TLI
7.753	8	0.458	0.969	0.944	0.956	1.003	1.003

$*p < 0.05, **p < 0.01$

Table 7: Structural Equation Model Fitting Index

In Table 7, we can see that χ^2/df is smaller than 3, GFI is smaller than 0.9; RMSEA is smaller than 0.1; RMR is smaller than 0.05; CFI, NFI, NNFI and TLI are all greater than 0.9 so the language structural equation model fits well.

2. Social Cognition Analysis in Eye-tracking Task
   Eye-tracking Tasks including figures task and false belief task, therefore a total of 5 variables. Firstly, there is a significant correlation between bilingual exposure and the dwell time to interacting figures in autistic children and Dwell time to interacting figures and to non-interacting figures have significant positive relationship. So I use Bootstrap sampling to test the intermediary effect and the path is shown in Figure 19.

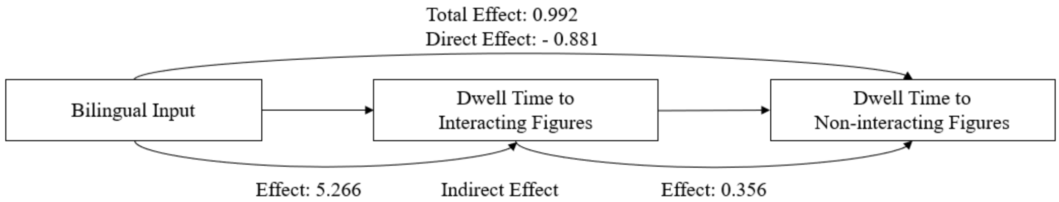

Figure 19: Social Cognitive Model Path Diagram

The model equations are shown as follows.

$$\text{time-interacting} \sim \text{bilingual-exposure}$$
$$\text{time-non-interacting} \sim \text{bilingual-exposure}$$
$$\text{time non-interacting} \sim \text{bilingual-exposure} + \text{time-interacting}$$

After 5000 samplings, I found that the 95% interval does not include the number 0 (95% CI: 0.175 4.499), indicating that bilingual exposure can affect dwell time to interacting figures first, and then through it to affect dwell time to not-interacting figures.

X	interacting figures	not interacting figures	not interacting figures
Constant	741.787(6.652**)	879.186(9.269**)	615.339(4.717**)
Bilingual exposure	5.266(2.890**)	0.992(0.640)	-0.881(-0.556)
interacting figures			0.356(2.724*)
R^2	0.188	0.011	0.184
AdjustR^2	0.166	-0.016	0.138
F (p-value)	8.354(0.006)	0.410(0.526)	3.951(0.028)

$*p < 0.05, **p < 0.01$

Table 8: Mediating Effect Model in Figure Task

The results show that if the time for bilingual input of autistic children increases by 1 point, the dwell time to interacting figures increases by 5.27 ms and to non interacting figures increase by 1 ms. Bilingual education will promote autistic children's interest in social interaction.

In False Belief Task, preference score is the total time to correct trial minus total looking time to incorrect trial and it has no correlation with other variables. Besides, there is no difference in the performance of children with bilingual exposure of low, medium and high in False Belief Task, KMO of principal component analysis is smaller than 0.5 and cannot pass Bartlett's sphericity test so I think bilingualism has no effect on false belief tasks.

6 Bilingual Exposure Influence on Executive Function

6.1 Correlation & Factor Analysis

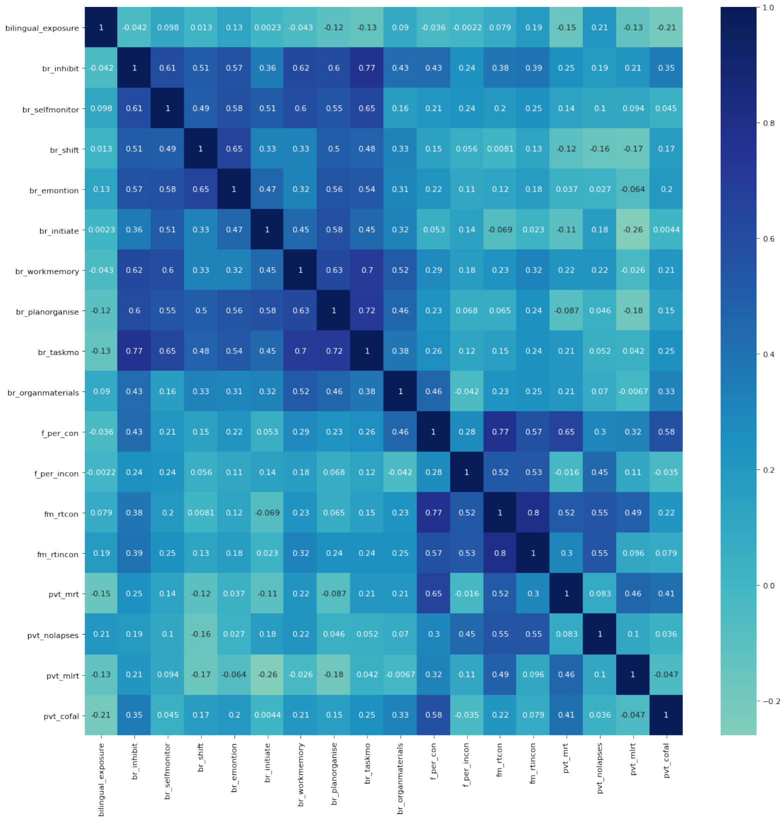

Figure 20: Correlation Analysis in Autistic Group

There is a total of 17 variables from BRIEF, the Flanker task and PVT, I first conduct factor analysis using total data sample and autistic data sample respectively to explore the relationship between variables.

Sample	factors	KMO	χ^2	df	p-value	Cumulative variance rate
Autistic(35)	3	0.791	245.472	78	0.00	69.190%
Total data(86)	3	0.858	758.760	78	0.000	73.234%

Table 9: Factor Analysis Results

Note that I delete No. 1019, 1040, 1051 autistic children for they have missing data in all executive function tests. From Table 9, the KMO is greater than 0.6 and the data passed the Bartlett sphericity test($p < 0.05$), indicating that the research data is suitable for factor analysis. Combined with the correlation relationship in Figure 17, variables in PVT shows very weak correlations and the data is volatile with high missing rate, therefore three 3 factors can be proposed to construct latent variables in model.

6.2 Executive Function Confirmatory Factor Analysis Model

Based on the analysis above, the structural equation model path analysis diagram is in Figure 21.

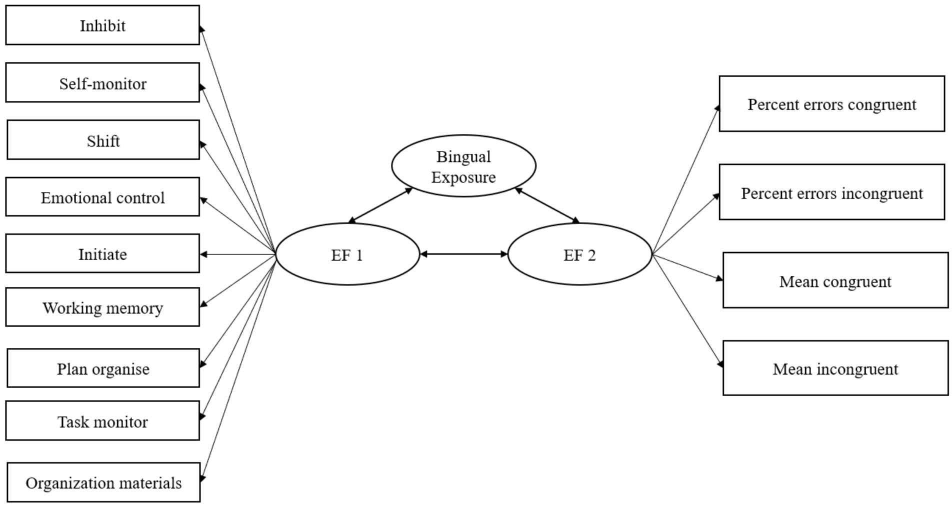

Figure 21: Confirmatory Factor Analysis Model Path Diagram

Initial Model

Latent Variable 1:
EF1 ~Inhibit + Self-monitor + Shift + Emotional control + Initiate + Working memory + Plan organise + Task monitor + Organization of materials
Latent Variable 2:
EF2 ∼ Percentage of errors in congruent trials + Percentage of errors in in congruent trials + Mean reaction time of correct responses in congruent trials + Mean reaction time of correct responses in congruent trials
EF1 ∼ Bilingual Exposure
EF2 ∼ Bilingual Exposure

However, I check the initial model and find that it is not converge. So I adjust it and fit the sample data with a reasonable model in autistic group and non-autistic group.

Confirmatory Factor Analysis Model

Latent Variable EF1:
EF1 ∼ Inhibit + Self-monitor + Shift + Emotional control + Working memory + Plan organise
Latent Variable EF2:
EF2 ∼ Mean reaction time of correct responses in congruent trials + Mean reaction time of correct responses in congruent trials
EF1 ∼ Bilingual Exposure
EF2 ∼ Bilingual Exposure

The $\chi^2/df \approx 257/68 \approx 3.79$ which is smaller than 5 suggests that the model can reasonably reflect the information of the sample data set. I can also compare the difference through standardized estimate coefficients of models between autistic children and non-autistic children.

Model in Autistic Children

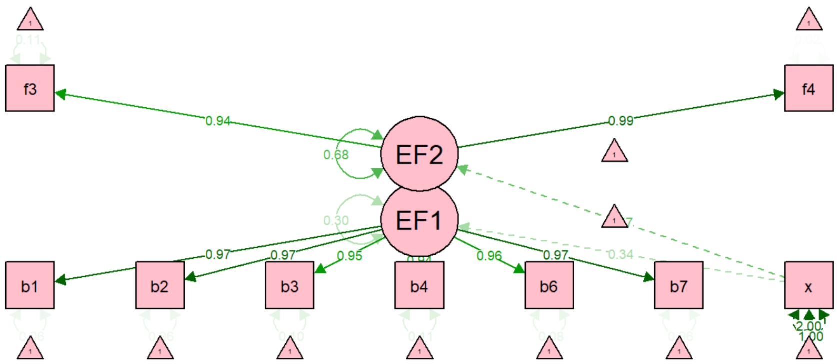

Figure 22: Executive Function Model in Autistic Children

Bilingual Exposure ~ EF1 ~ 0.126 * Inhibit + 0.068 * Self-monitor + 0.131 * Shift + 0.124 * Emotional control + 0.123 * Working memory + 0.124 * Plan organize

Bilingual Exposure ~ EF2 ~ 14.476* Mean reaction time of correct responses in congruent trials + 15.424 * Mean reaction time of correct responses in incongruent trials

Model in Non-autistic Children

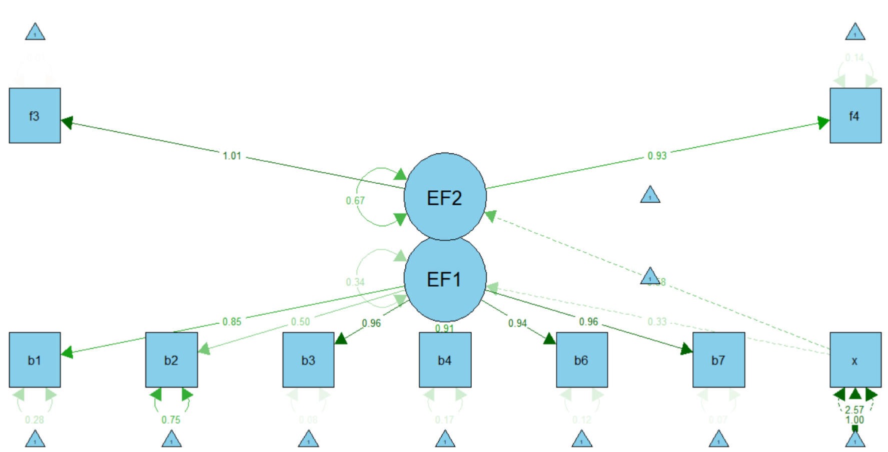

Figure 23: Executive Function Model in Non-autistic Children

Bilingual Exposure ~ EF1 ~ 0.086 * Inhibit + 0.51 * Self-monitor + 0.077 * Shift + 0.082 * Emotional control + 0.077 * Working memory + 0.084 * Plan organize

Bilingual Exposure ~ EF2 ~ 14.2* Mean reaction time of correct responses in congruent trials + 15.916 * Mean reaction time of correct responses in in-congruent trials

From the results of models above, bilingual exposure has a positive effect on autistic children's executive function ability since all the coefficients are greater than zero. For autistic children, if the proportion of bilingual input time increases by 1%, the inhibition of the autistic children increases by 0.126 points, and their self-monitor ability increases by 0.31 points. At the same time, their emotional control ability, working memory, plan organize ability will also improve 0.124, 0.123 and 0.123 respectively. In the BRIEF test results, it is known from the comparison of the fitting coefficients of the model that under the same bilingual exposure level, compared with non-autistic children, except that the improvement in self-management ability is less than that of non-autistic children. ($0.51 > 0.068$), bilingual exposure promotes the executive function of autistic children more obviously.

Besides, from the latent variable EF2, we can find that bilingual exposure can greatly increase the mean reaction time of correct responses in both congruent and in congruent trials. There is no apparent difference of bilingual effects between groups.

7 Conclusions

Firstly, early exposure to bilingual autistic children is stronger in inhibit, task monitor an inhibit executive function than later exposure children. There is a positive correlation between bilingual exposure and IQ for children with autism. Bilingual exposure can enhance their language ability through positive influence on intelligence. With increased bilingual exposure dose level, the language processing speed is increased and the English vocabulary score obtained by autistic children in BPVS will also increase.

Besides, bilingual environment will promote autistic children's interest in social interaction to a certain extent since bilingual exposure has a positive effect in TOMI and TOMB results. it can benefit autistic children in social cognition fields. For example, I find that if the time for bilingual input of autistic children increases by 1 point, the dwell time to interacting figures increases by 5.27 ms which suggests bilingual environment will promote autistic children's interest in social interaction. I find that bilingual contact may have an impact on the inhibition of autistic children, but it will not reduce the speed of their correct response but can helps improve the response speed of autistic children to goals.

In executive function field, bilingual contact has a stronger positive effect on autistic children compared with non-autistic children, especially in the aspect of Behavioural Regulation (Inhibit, shift and emotional control). In addition, it can also benefit autistic children's working memory and plan and organize abilities of Metacognition.

In conclusion, bilingual environment has positive effects on autistic children in IQ, language, social cognition and executive function fields.

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Appendices

A Note

I deal missing data in R with mice package and combined with exploratory analysis. I think one limitation is that the sample is small and some missing values in PVT results could have extreme or special values than cannot be explore.

Besides, I also combine some basic statistic methods such as correlation analysis, comparative analysis, significant test,path analysis and mediation test to analyse the data from different directions but the conclusions may be a little bit messy.

And I mainly use Confirmatory factor analysis, I tried PCA and factor analysis but sometimes KMO result is not ideal and regression model has bad performance. But I think do a cluster analysis according to autistic children's age or the age of they acquire the second language and compare the difference is also a good and simple way to explore data but the sample of autistic children is too small to divide into 3 groups. In fact, I have tried it.

In addition, when I write code, I combine different softwares including R, Python, SPSS and AMOS. I cannot put all my code and tables and data set and procedures here but I have tried my best to present it as smoothly as possible. After all, the process of adjusting the model is fast at that moment and each day is a new start! There are too many operations and data sets I rename them again and again.

Finally, it is my great honor to have been a student in Edinburgh. Many thanks to lectures and professors.

Best wishes for you!

B Python Code

```
# -*- coding: utf-8 -*-
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import mode
get_ipython().magic('matplotlib inline')
import datetime
from pandas import Series
from numpy import mean, median
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.sandbox.regression.predstd import wls_prediction_std
import seaborn as sns
sns.set_style("darkgrid")

df = pd.read_csv('C:/Users/Rainie Liu/Desktop/complete.csv')
# 'adf1'= autistic group, 38 children
adf = pd.read_csv('C:/Users/Rainie Liu/Desktop/adf1.csv')
# 'ndf1' = nonautistic group, 51 children
ndf = pd.read_csv('C:/Users/Rainie Liu/Desktop/ndf1.csv')
# Describe statistics
# autistic group vs nonautistic group
print(adf.describe())
print(ndf.describe())
adf.boxplot()
```

```
ndf.boxplot()
df['age_acquisition'].describe()
# Use levene to test the homogeneity of variance
stats.levene(adf, ndf)
# view correlations
adf.corr('spearman')
ndf.corr('spearman')
df['bpvs_raw'].describe()
df['vocabprocess_processing_speed_target'].describe()
# Independent Sample T-Test
# Bilingual Exposure Level
a = df[df['diagnosis']==1]['bilec_total_input']
n = df[df['diagnosis']==0]['bilec_total_input']
print(levene(a,n))
print(ttest_ind(a,n))
a = df[df['diagnosis']==1]['bilec_total_output']
n = df[df['diagnosis']==0]['bilec_total_output']
print(levene(a,n))
print(ttest_ind(a,n))
aIQ = df[df['diagnosis']==1]['wasi_sum_rawscores']
nIQ = df[df['diagnosis']==0]['wasi_sum_rawscores']
print(levene(aIQ,nIQ))
# p-value = 0.019 < 0.05,Variance is not equal
# IQ independent sample t test
print(ttest_ind(aIQ,nIQ,equal_var=False))
# p-value = 0.04857 < 0.05, There is difference in IQ levels between two groups
# Compare IQ
aIQ.describe()
nIQ.describe()
# Language compare in autistic/nonautistic group
# Language-vocabulary in autistic/ nonautistic group
# Test the homogeneity of variance of language vocabulary
av = df[df['diagnosis']==1]['bpvs_raw']
nv = df[df['diagnosis']==0]['bpvs_raw']
print(levene(av,nv))
# p-value = 0.000253898 < 0.05, Variance is not equal
# Vocabulary independent sample t test
print(ttest_ind(av,nv,equal_var=False))
# p-value = 0.1114145 > 0.05, there is no significant difference in vocabulary
#between the autistic group and the nonautistic group
# Language-speed in autistic/ nonautistic group
# Test the homogeneity of variance in language processing speed
aspeed = df[df['diagnosis']==1]['vocabprocess_processing_speed_target']
nspeed = df[df['diagnosis']==0]['vocabprocess_processing_speed_target']
print(levene(aspeed,nspeed))
# p-value  > 0.05, Variance is equal
# Vocabulary process speed independent sample t test
print(ttest_ind(aspeed,nspeed))
# Social Function
# Do same T-test of variables in TOM,TOMI test
a = df[df['diagnosis']==1]['et_figurestask_dwell_time_interacting']
n = df[df['diagnosis']==0]['et_figurestask_dwell_time_interacting']
print(levene(a,n))
print(ttest_ind(a,n))

a = df[df['diagnosis']==1]['et_falsebelief_Testtrial_dwell_time_to_correct']
n = df[df['diagnosis']==0]['et_falsebelief_Testtrial_dwell_time_to_correct']
print(levene(a,n))
print(ttest_ind(a,n,equal_var=False))
print(ttest_ind(a,n))
a = df[df['diagnosis']==1]['et_falsebelief_testtrial_preference_score']
n = df[df['diagnosis']==0]['et_falsebelief_testtrial_preference_score']
print(levene(a,n))
print(ttest_ind(a,n))
# Correlation analysis between variables
# SC, EF compare in autistic/nonautistic group
```

```
# 'aSC1' and 'nSC1' contains variables in TOM, TOMI,ET results
# 'aEF1' and 'aEF2' contains variables in BRIEF,FLANKER,PVT of
# Draw Correlation coefficient heatmap of Social Cognition
def heatmap(data, method='pearson', camp='YlGnBu', figsize=(10 ,8), ax=None):
    plt.figure(figsize=figsize, dpi= 80)
    sns.heatmap(data.corr(method=method),
                xticklabels=data.corr(method=method).columns,
yticklabels=data.corr(method=method).columns, cmap=camp,
center=0, annot=True, ax=ax)
heatmap(asc)
heatmap(nsc)
# Draw Correlation coefficient heatmap of Executive Function
def test(df):
    dfData = df.corr()
    plt.subplots(figsize=(10, 10)) # Set screen size
    sns.heatmap(dfData, annot=True, vmax=1, square=True)
    plt.show()
test(aef)
test(nef)
# OLS:
inhibit_modela= ols("brief_raw_inhibit ~ bilec_home_output
            + bilec_total_input + bilec_total_output + diagnosis",data=df).fit()
inhibit_modeln= ols("brief_raw_inhibit ~ bilec_home_output
            + bilec_total_input + bilec_total_output + diagnosis",data=df).fit()
inhibit_model_summary = inhibit_model.summary()
print(inhibit_model_summary)
```

C R Code

```
library(lattice)
library(lavaan)
library(MASS)
library(nnet)
library(psych)
library(mice)
library(VIM)
rm(list=ls())
# ;;--------------------------------------------------
# ;;-------------------------------------------------
# Data set
# ;;--------------------------------------------------
# ;;-------------------------------------------------
# 'adf1' is the data set of autistic group
adf1 <- read.csv('C:/Users/Rainie␣Liu/Desktop/adf1.csv', header = TRUE)
# 'ndf1' is the data set of non-autistic group
ndf1 <- read.csv('C:/Users/Rainie␣Liu/Desktop/ndf1.csv', header = TRUE)
# 'SC' data set includes TOM,TOMI,ET test results
SC <-  read.csv('C:/Users/Rainie␣Liu/Desktop/SC.csv', header = TRUE)
# 'EF' data set includes BRIEF,FLANKER,PVT test results
EF <- read.csv('C:/Users/Rainie␣Liu/Desktop/EF.csv', header = TRUE)

summary(adf1)
summary(ndf1)

# ;;--------------------------------------------------
# ;;--------------------------------------------------
# Deal missing data
# ;;--------------------------------------------------

aggr_plot <- aggr(SC, col= c('navyblue','red'),
labels = names(SC),cex.axis = .2,
```

```
gap = 3, ylab = c("Histogram␣of␣missing␣data","Pattern"))
marginplot(SC[c(1,2)])
aggr_plot <- aggr(EF, col= c('navyblue','red'),
labels = names(EF),cex.axis = .2,
gap = 3, ylab = c("Histogram␣of␣missing␣data","Pattern"))

# Social Cognition imputation
#impute missing data use PMM method and get 5 complete data set
adf_temp <- mice(adf1,m=5,maxit=50,meth='pmm',seed=500)
ndf_temp <- mice(ndf1,m=5,maxit=50, meth = 'pmm',seed = 500)

# see imputation in variable 'brief_raw_organisation_of_materials'
ndf_temp$imp$brief_raw_organisation_of_materials

#Take a look at the first and second column variables
xyplot(adf_temp, tom_tb_totalscore ~ age_m + bpvs_raw
+vocabprocess_processing_speed_target
+wasi_sum_rawscores,pch=18,cex=1)

# use impute the 3rd data set to get a complete data set
# Social Cognition
# and BRIEF task
adf_comp <- complete(adf_temp, 3)
ndf_comp <- complete(ndf_temp, 3)

#look at each impute value and use the 3rd values
# impute missing data in PVT and flanker task with PMM
adf_temp$imp$pvt_count_falsestarts
ndf_temp$imp$pvt_count_falsestarts

# 'impdata' only has missing values in Flanktask and PVT test
impdat <- read.csv('C:/Users/Rainie␣Liu/Desktop/impdata.csv', header = TRUE)

# pairwise delete part_nu = 1019,1040,1051 when analyse executive function
# ;;-----------------------------------------------
# ;;----------------------------------------------
# high correlation between Flankertask and PVT results
# use regression to impute missing values
# ;;-----------------------------------------------
# ;;----------------------------------------------
linear_model1 <- lm(flanker_percenterrors_congruent ~ pvt_mean_rt
+ pvt_number_of_lapses + pvt_mean_lapse_rt
+ pvt_count_falsestarts, data = impdat)
abline(linear_model1,col="red")
summary(linear_model1)
#use mice to impute missing values in Flanker task
imp <- mice(impdat,seed=500)
fit_new <- with(imp,linear_model1 )
pooled <- pool(fit_new)
#acquire new data set1
new_data <- complete(imp,action=3)
#impute missing values in 'flanker_percenterrors_congruent'
new_data$flanker_percenterrors_congruent
# ;;-----------------------------------------------
# ;;----------------------------------------------
linear_model2 <- lm(flanker_percenterrors_incongruent ~ pvt_mean_rt
+ pvt_number_of_lapses + pvt_mean_lapse_rt
+ pvt_count_falsestarts, data = impdat)
abline(linear_model2,col="red")
summary(linear_model2)
```

```
#use mice to impute missing values in Flanker task
imp <- mice(impdat,seed=500)
fit_new2 <- with(imp,linear_model2 )
pooled <- pool(fit_new2)
#acquire new data set1
new_data2 <- complete(imp,action=3)
#impute missing values in 'flanker_percenterrors_incongruent'
new_data2$flanker_percenterrors_incongruent
# ;;-----------------------------------------------
# ;;----------------------------------------------
linear_model3 <- lm(flanker_mean_rt_congruent ~ pvt_mean_rt
+ pvt_number_of_lapses + pvt_mean_lapse_rt
+ pvt_count_falsestarts, data = impdat)
abline(linear_model3,col="red")
summary(linear_model3)
#use mice to impute missing values in Flanker task
imp <- mice(impdat,seed=500)
fit_new3 <- with(imp,linear_model3 )
pooled <- pool(fit_new3)
#acquire new data set1
new_data3 <- complete(imp,action=3)
#impute missing values in 'flanker_mean_rt_congruent'
new_data3$flanker_mean_rt_congruent
# ;;-----------------------------------------------
# ;;----------------------------------------------
linear_model4 <- lm(flanker_mean_rt_incongruent ~ pvt_mean_rt
+ pvt_number_of_lapses + pvt_mean_lapse_rt
+ pvt_count_falsestarts, data = impdat)
abline(linear_model4,col="red")
summary(linear_model4)
#use mice to impute missing values in Flanker task
imp <- mice(impdat,seed=500)
fit_new4 <- with(imp,linear_model4 )
pooled <- pool(fit_new4)
#acquire new data set1
new_data4 <- complete(imp,action=3)
#impute missing values in 'flanker_mean_rt_incongruent'
new_data4$flanker_mean_rt_incongruent
# ;;-----------------------------------------------
# ;;----------------------------------------------
# MODEL EXECUTIVE FUNCTION MODEL
# ;;-----------------------------------------------
# ;;----------------------------------------------
# Executive function Models, data set 't1' only includes
# 'x' : total input          ' diagnosis'
# b1~b9 from BRIEF Test, f1~f4 from Flanker task
# from 35 autistic children and 51 nonautistic children
# ;;-----------------------------------------------
# ;;-----------------------------------------------
df <- read.csv('C:/Users/Rainie␣Liu/Desktop/t1.csv', header = TRUE)
model <- '␣␣EF␣=~␣1*b1␣+␣b2␣+b3␣+␣b4␣+b6␣+b7␣+␣b8␣+␣b9
+␣f1␣+␣f2␣+␣f3␣+␣f4
␣␣␣␣␣␣␣␣␣␣␣␣EF␣~␣1*x
␣␣␣␣␣␣␣␣␣␣␣␣EF␣~~␣EF
␣␣␣␣␣␣␣␣␣␣␣␣EF␣~␣X
␣␣␣␣␣␣␣␣␣␣␣␣b1␣~~␣b1
␣␣␣␣␣␣␣␣␣␣␣␣b2␣~~␣b2
␣␣␣␣␣␣␣␣␣␣␣␣b3␣~~␣b3
␣␣␣␣␣␣␣␣␣␣␣␣b4␣~~␣b4
␣␣␣␣␣␣␣␣␣␣␣␣b6␣~~␣b6
␣␣␣␣␣␣␣␣␣␣␣␣b7␣~~␣b7
```

```
␣␣␣␣␣␣␣␣␣␣␣␣b8␣~~␣b8
␣␣␣␣␣␣␣␣␣␣␣␣b9␣~~b9
␣␣␣␣␣␣␣␣␣␣␣␣f1␣~~␣f1
␣␣␣␣␣␣␣␣␣␣␣␣f2␣~~␣f2
␣␣␣␣␣␣␣␣␣␣␣␣f3␣~~f3
␣␣␣␣␣␣␣␣␣␣␣␣f4␣~~f4
␣␣␣␣␣␣␣␣␣␣␣␣x␣~~␣x'

fit1 <- lavaan(model, data = df, group = "diagnosis")
summary(fit1)
fitMeasures(fit1,c("chisq","df","pvalue","cfi","nfi","ifi","rmsea","EVCI"))
# not converge

parameterEstimates(fit,ci=FALSE,standardized = TRUE)

#----------------------------------------------------
model <- '␣␣EF1␣=~␣NA*b1␣+␣b2␣+␣b3␣+␣b4␣+b6␣+b7␣+␣b8␣+␣b9
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣=~␣NA*f3␣␣+␣f4
␣␣␣␣␣␣␣␣␣␣␣␣EF1␣~␣1*x
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣~␣1*x
␣␣␣␣␣␣␣␣␣␣␣␣EF1␣~~␣EF1
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣~~␣EF2
␣␣␣␣␣␣␣␣␣␣␣␣b1␣~~␣b1
␣␣␣␣␣␣␣␣␣␣␣␣b2␣~~␣b2
␣␣␣␣␣␣␣␣␣␣␣␣b3␣~~␣b3
␣␣␣␣␣␣␣␣␣␣␣␣b4␣~~␣b4
␣␣␣␣␣␣␣␣␣␣␣␣b6␣~~␣b6
␣␣␣␣␣␣␣␣␣␣␣␣b7␣~~␣b7
␣␣␣␣␣␣␣␣␣␣␣␣b8␣~~␣b8
␣␣␣␣␣␣␣␣␣␣␣␣b9␣~~b9
␣␣␣␣␣␣␣␣␣␣␣␣f3␣~~␣f3
␣␣␣␣␣␣␣␣␣␣␣␣f4␣~~␣f4'

fit2 <- lavaan(model, data = df, group = 'diagnosis')
summary(fit2)
fitMeasures(fit2,c("chisq","df","pvalue","cfi","nfi","ifi","rmsea","EVCI"))
#chisq      df   pvalue     cfi     nfi     ifi    rmsea
#441.197 128.000   0.000   0.295   0.234   0.301   0.239
#CHISQ/DF = 3.89

#----------------------------------------------------
#----------------------------------------------------
model2 <- '␣␣EF1␣=~␣NA*b1␣+␣b3␣+␣b4␣+b6␣+b7␣+␣b8␣+␣b9
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣=~␣NA*f3␣␣+␣f4
␣␣␣␣␣␣␣␣␣␣␣␣EF1␣~␣1*x
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣~␣1*x
␣␣␣␣␣␣␣␣␣␣␣␣EF1␣~~␣EF1
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣~~␣EF2
␣␣␣␣␣␣␣␣␣␣␣␣b1␣~~␣b1
␣␣␣␣␣␣␣␣␣␣␣␣b3␣~~␣b3
␣␣␣␣␣␣␣␣␣␣␣␣b4␣~~␣b4
␣␣␣␣␣␣␣␣␣␣␣␣b6␣~~␣b6
␣␣␣␣␣␣␣␣␣␣␣␣b7␣~~␣b7
␣␣␣␣␣␣␣␣␣␣␣␣b8␣~~␣b8
␣␣␣␣␣␣␣␣␣␣␣␣b9␣~~b9
␣␣␣␣␣␣␣␣␣␣␣␣f3␣~~␣f3
␣␣␣␣␣␣␣␣␣␣␣␣f4␣~~␣f4'

fit <- lavaan(model, data = df, group = 'diagnosis')
summary(fit)
fitMeasures(fit,c("chisq","df","pvalue","cfi","nfi","ifi","rmsea","EVCI"))
```

```
# chisq      df   pvalue     cfi     nfi     ifi    rmsea
# 355.990  86.000   0.000   0.203   0.170   0.213   0.270
# ;---------------------------------------------------
model <- '␣␣EF1␣=~␣NA*b1␣+␣b2␣+␣b3␣+␣b4␣+b6␣+b7
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣=~␣NA*f3␣␣+␣f4
␣␣␣␣␣␣␣␣␣␣␣␣EF1␣~␣1*x
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣~␣1*x
␣␣␣␣␣␣␣␣␣␣␣␣EF1␣~␣1*EF2
␣␣␣␣␣␣␣␣␣␣␣␣EF1␣~~␣EF1
␣␣␣␣␣␣␣␣␣␣␣␣EF2␣~~␣EF2
␣␣␣␣␣␣␣␣␣␣␣␣b1␣~~␣b1
␣␣␣␣␣␣␣␣␣␣␣␣b2␣~~␣b2
␣␣␣␣␣␣␣␣␣␣␣␣b3␣~~␣b3
␣␣␣␣␣␣␣␣␣␣␣␣b4␣~~␣b4
␣␣␣␣␣␣␣␣␣␣␣␣b6␣~~␣b6
␣␣␣␣␣␣␣␣␣␣␣␣b7␣~~␣b7
␣␣␣␣␣␣␣␣␣␣␣␣f3␣~~␣f3
␣␣␣␣␣␣␣␣␣␣␣␣f4␣~~␣f4'
fit <- lavaan(model, data = df, group = 'diagnosis')
summary(fit)
fitMeasures(fit,c("chisq","df","pvalue","cfi","nfi","ifi","rmsea","EVCI"))
#   chisq  df  pvalue     cfi     nfi     ifi   rmsea
# 257.543  68.000   0.000   0.254   0.210   0.265   0.255
# ;;--------------------------------------------------
# ;;--------------------------------------------------
# --------------------------------------------------
semPaths(fit,layout = "tree2")
semPaths(fit,what = "eq",layout = "tree")
semPaths(fit,color= "pink",what="path",layout = "circle")

semPaths(fit3,what = "est",layout = "spring")
semPaths(fit3,what = "est",layout = "circle")

############################ Model EXPLORE........
# ;;--------------------------------------------------
# ;;--------------------------------------------------
# SEM-----------------------------------------------
# Latent variable:SC1,SC2,SC3,SC4,
# Latent variable:EF1,EF2,EF3,EF4
# Latent variable: X
#---Bilingualism-----------------------------------
# Set the variance of the latent variable to 1
model <- 'SC1␣=~␣tomi_early␣+␣tomi_basic
+␣tomi_advanced␣+␣tomi_compmean␣+␣tom_tb_totalscore
SC2␣=~et_falsebelief_testtrial_dwell_time_to_incorrect
+et_falsebelief_testtrial_preference_score
SC3␣=~et_falsebelief_Testtrial_dwell_time_to_correct
+et_falsebelief_testtrial_preference_score
SC4␣=␣et_figurestask_dwell_time_interacting
+et_figurestask_dwell_time_not_interacting
␣␣␣␣␣␣␣␣␣␣␣␣SC1␣~␣bilec_total_input
␣␣␣␣␣␣␣␣␣␣␣␣SC2␣~␣bilec_total_input
␣␣␣␣␣␣␣␣␣␣␣␣SC3␣~␣bilec_total_input
␣␣␣␣␣␣␣␣␣␣␣␣SC4␣~␣bilec_total_input
␣␣␣␣␣␣␣␣␣EF1=~brief_raw_shift+brief_raw_emotional_control
␣␣␣␣␣␣␣␣␣+brief_raw_initiate+brief_raw_working_memory
␣␣␣␣␣␣␣␣␣+brief_raw_plan_organise+brief_raw_task_monitor
␣␣␣␣␣␣␣␣␣+brief_raw_organisation_of_materials
EF2=~flanker_percenterrors_congruent
+flanker_percenterrors_incongruent+flanker_mean_rt_congruent
+flanker_mean_rt_incongruent+pvt_number_of_lapses
```

```
EF3=~flanker_percenterrors_congruent+pvt_mean_rt
+pvt_number_of_lapses+pvt_mean_lapse_rt
+pvt_count_falsestarts
EF4=~brief_raw_inhibit+brief_raw_self+␣pvt_count_falsestarts
EF1␣~␣bilec_total_input
EF2␣~␣bilec_total_input
EF3␣~␣bilec_total_input
EF4␣~␣bilec_total_input'

fit <- sem(model,data = df,group = "diagnosis")
summary(fit)
#see plots
semPlot::semPaths(fit,what = "standard")
#acquire estimatiors dataframe
parameterEstimates(fit,ci=FALSE,standardized = TRUE)
#see plots
semPaths(fit, what = "est")
standardizedSolution(fit)

model <- 'EF1=~brief_raw_shift+brief_raw_emotional_control
+brief_raw_initiate+brief_raw_working_memory
+brief_raw_plan_organise+brief_raw_task_monitor
+brief_raw_organisation_of_materials
EF2=~flanker_percenterrors_congruent
+flanker_percenterrors_incongruent
+flanker_mean_rt_congruent+flanker_mean_rt_incongruent
+pvt_number_of_lapses
EF3=~flanker_percenterrors_congruent+pvt_mean_rt
+pvt_number_of_lapses+pvt_count_falsestarts
EF4=~brief_raw_inhibit+brief_raw_self+␣pvt_count_falsestarts
EF1␣~␣bilec_total_input
EF2␣~␣bilec_total_input
EF3␣~␣bilec_total_input
EF4␣~␣bilec_total_input'
```