Original article

Investigation of factors affecting the intelligence quotient (IQ) of intellectually disabled children and adolescents using modern regression approaches

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Abstract

Background: Research shows that in addition to biological factors, psychological and social risk factors play a role in the development of intellectual disability.

Objectives: This study aimed to investigate the familial, personal and educational factors affecting the intelligence quotient (IQ) levels of intellectually disabled children and adolescents via regularized regression approaches (RRAs) and to compare the results with those of conventional regression approach (CRA).

Methods: A total of sixty characteristics were examined along with dummy variables of 205 children and adolescents selected according to the study protocol. Compact, Lasso, Ridge and Ridged Lasso RRAs were used in the dataset.

Results: The optimal model was obtained with the Lasso approach and contained ten risk factors having a significant effect on IQ levels: diagnosis of cerebral palsy, age at onset of speech, duration of education, age at onset of walking, presence of elimination disorders, presence of attention-deficit hyperactivity disorder, family income, and number of siblings, residence and age. The RRAs provided opportunity to examine more factors than CRAs without requiring the fulfillment of strict CRA assumptions.

Conclusions: Due to the advantages of RRAs, expanding their clinical usage for very large datasets was recommended. [*Ethiop. J. Health Dev.* 2018;32(1):21-28]

Keywords: Intelligence quotient, intellectual disability, regularized regression, Lasso, Ridged Lasso

Introduction

Intellectual disability, originally called mental retardation, is defined as incompetence/limitedness at a significant level in at least two adaptive behaviors developing in intellectual functions and cognitive, social, practical and adaptive skills of an individual diagnosed before age 18. Chromosomal abnormalities are the most common causes (40%) of intellectual disability (2). Known causes include infection, diseases affecting the central nervous system, external factors such as trauma and toxins, and some birth traumas occurring during delivery, prolonged delivery and premature labor. In addition, studies show that in addition to biological factors, psychological and social risk factors play a role in the development of intellectual disability (2-4).

Although diagnosis is made in particular areas like psychiatry and clinical psychology, the severity of the condition may increase due to environmental factors triggering the health issues of an individual (5). In addition to diagnosis, it is important to determine the factors considered to cause the condition or to affect its persistence. Therefore, when there are a large number of characteristics to be examined but only a few observations (subjects), i.e., a very large and high-dimensional dataset, simultaneous investigation of all variables and their effects becomes difficult or impossible using conventional statistical methods. In such cases, information would be lost, and the resulting model would not reflect the real world. However, a large number of predictors and subjects can be assessed and successful predictions performed in cases where the number of predictors is greater than the number of subjects. High correlations between predictors do not constitute a problem, and simpler but more successful results can be seen in predictions obtained via the modern regression models introduced in recent years within the scope of data mining methods. Thus, these results reflect the real world better than those obtained with the conventional regression models (6,7). Regularized regression approaches (RRAs) include regression methods regularized against the difficulties encountered by conventional regression approaches (CRAs) (7,8). The use of RRAs avoids the loss of information when a large number of variables are to be examined simultaneously in health field studies, and at the same time the use of these approaches ensures accurate, unbiased, consistent and effective parameter estimates. In the literature, a limited number of studies can be found utilizing modern regression models in the medical field (9-12).

The present study aimed to investigate familial, personal and educational factors affecting intelligence quotient (IQ) scores representing the intelligence level of intellectually disabled children and adolescents. Studies on this topic in the literature have utilized

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classical statistical models; thus, with the goal of achieving more realistic results, the risk factors obtained via RRAs were evaluated and compared with those obtained using CRA.

Materials and Methods

***Subjects and design*:** All intellectually disabled children and adolescents who applied to the Psychiatry Polyclinic of the Duzce University Medical Faculty between November 2011 and August 2013 were included in the research group. Between these specified dates, 205 of a total of 350 children brought by their parents or institutions (SSI, counseling centers, schools) due to intellectual disability were diagnosed as mentally retarded based on DSM-IV-TR criteria (13). Children who were visually and/or hearing impaired or who had an IQ level above 80 were not included in the study. Data were collected by means of clinical interviews, observations and questionnaires. The term “mental retardation” in DSM-IV-TR has been revised as “intellectual disability (intellectual developmental disorder)” in DSM-V criteria (13,14). Along with this change, in DSM-V the greater part of intellectual disability is assessed according to adaptive qualities instead of the intelligence scores obtained from tests. In the United States, the term "intellectual disability" is preferred in certain medical, academic and other application areas, because it avoids stigma by putting more emphasis on “disability”. Therefore, the term “intellectual disability” has been used in this study. This study was approved by the local Ethical Committee Board (Duzce University, Duzce, Turkey).

Data-collection tools:

a) ***Questionnaire***: Data was collected from children diagnosed as mentally retarded and their parents via a questionnaire form on sociodemographic attributes, which included the age of the child, number of children, presence of intellectual disability in the family, education levels of parents, number of siblings, primary caretaker, special education status, family income, diseases in infancy, duration of child’s education, reading-writing-mathematics levels of child, mode of delivery, age at onset of speech and walking and the presence of elimination disorders.
b) Since there was only one individual with a high-school graduate mother, elementary school and high school levels were combined for this variable. Similarly, since there was only one child whose mathematics level was “good”, level combination was also applied for this variable.
c) Attention-deficit hyperactivity disorder (ADHD) diagnostic criteria: In order to determine the presence and level of ADHD in the children, ADHD diagnostic scales were administered to the parents. The diagnosis was considered as positive in cases where six of the nine items on the ADHD scale were present. The levels of ADHD were specified as slight, moderate and severe (13). The ADHD criteria in DSM-V are quite similar to those in DSM-IV-TR. However, the diagnostic criteria for impairment in DSM-V have been further strengthened. For example, in DSM-V, more emphasis has been put on the fact that the appearance of impairment may vary in different cultures (14).
d) ***Porteus maze test***: In this test, subjects are asked to find the exit from the maze as soon as possible by starting from the letter S in the maze and without crossing through solid lines with their pen. In order to be successful in this test, good planning is required and blind alleys in the maze must be considered. In the Porteus maze test, scores are based on the performance, and the intelligence level is determined (15).

Regularized regression approaches (RRAs): Since RRAs fall within the data mining group and are constructed to eliminate the difficulties encountered in classical approaches in order to obtain more realistic results, they are also known as regularized regression models (RRMs), which include Compact, Lasso, Ridged Lasso and Ridge regression models (7,16,17). Ridge regression is the oldest method found in the literature and was developed for accurate prediction of coefficients in the presence of multicollinearity problems (variables with high correlation) in datasets containing a large number of predictor variables. The Lasso regression model has come into common usage recently, especially for large datasets, and has been developed as a simplified version of the Ridge regression model. The Compact regression model is a forward stepwise regression approach which builds a model with as few variables as possible. All of these models can also be used as variable selection methods. Depending on the algorithms, the model is made up only of meaningful variables that contribute to the model (7,16,18). Regression coefficients of RRMs are regulated by means of an elastic coefficient. The power on the regression coefficient (β) is called the “elasticity” value. Elasticity coefficient values range from 0 to 2, representing the weight of Compact [0], Lasso [1], and Ridge [2] optimizations (18).

The performance of the generated regression models were assessed based on the results obtained from the test dataset. A 10-fold cross-validation method was used in the selection of the test data in this study. The optimum model was the one giving the lowest mean squared error (MSE) value in the test data. In addition, R^2, mean absolute deviation (MAD), mean relative absolute deviation (MRAD), Akaike information criterion (AIC), corrected Akaike information criterion (AICc) and Bayesian information criterion (BIC) were also used as other model fit indices in the selection of the optimum model (8).

Dummy predictors for each categorical characteristic were created and 60 characteristics (23 predictors + 27 dummy predictors) in total were included in the study. This study was performed by using the Generalized Path Seeker options of SPM trial program (18) and SPSS v.22.

Results

In this study, 42% (n=86) of the children and adolescents aged 6 - 20 (10.52 ± 3.16) with intellectual disability were female and 58% (n=119) were male, 36% (n=73) had an education for 1-2 years and only 2% (n=4) had 9-11 years of education. It was revealed that 154 children (75%) lived in rural areas and 68% (n=138) of the families had low incomes (one or less than one monthly minimum wage). The descriptive values of personal, familial and educational characteristics of the children and adolescents included in the study are given in detail in Tables 1 and 2.

Table 1: **Descriptive values of personal characteristics of children and adolescents with intellectual disability**

Personal Characteristics		Number	Percent
Age (n = 205)#	10.52±3.16 (6-20)		
Age at onset of speech (n = 163)#	3.98±1.61 (1-10)		
Age at onset of walking (n = 195)#	3.08±1.43 (1-10)		
Intelligence level (n = 205)#	53.52±11.69 (18-80)		
Gender	Male	119	58.05
	Female	86	41.95
Number of siblings	1	85	41.46
	2	56	27.32
	3	30	14.63
	4	19	9.27
	5	8	3.90
	6	4	1.95
	7	1	0.49
	8	2	0.98
Special education	Yes	32	15.61
	No	173	84.39
Years of education	0	26	12.75
	1-2	73	35.78
	3-5	71	34.80
	6-8	30	14.71
	9-11	4	1.96
Reading level	Absent	150	73.17
	Poor	24	11.71
	Good	31	15.12
Writing level	Absent	155	75.61
	Poor	26	12.68
	Good	24	11.71
Mathematics level	Absent	192	93.66
	Poor	13	6.34
Mode of delivery	Normal delivery	102	49.76
	Preterm delivery	23	11.22
	Difficult delivery	46	22.44
	Cesarean delivery	34	16.59
Diseases in infancy	Convulsion	60	29.27
	Epilepsy	29	14.15
	Other*	10	4.88
	None	106	51.71
Cerebral palsy	Yes	194	94.63
	No	11	5.37
ADHD	Slight	20	9.76
	Moderate	32	15.61
	Severe	26	12.68
	None	127	61.95
Behavioral disorders	Yes	27	13.17
	No	178	86.83
Elimination disorders	Primary enuresis	46	22.44
	Mixed	15	7.32
	Secondary	4	1.95
	None	140	68.29

#: Mean ± Standard Deviation (minimum-maximum), ADHD: Attention-Deficit Hyperactivity Disorder,
*: Traffic accident, autism, congenital heart defect

Table 2: **Descriptive values of familial characteristics of children and adolescents with intellectual disability**

Familial Characteristics		**Number**	**Percent**
Number of children (n=205)#	3.23±1.51 (1-8)		
Presence of intellectual disability in family	Mother	16	7.84
	Father	18	8.82
	None	170	83.33
Primary caretaker	Mother	181	88.73
	Other	23	11.27
Residence	City center	51	24.88
	District	69	33.66
	Village	85	41.46
Education level of mother	Uneducated	144	70.59
	Educated	60	29.41
Education level of father	Uneducated	102	50.25
	Educated	101	49.75
Income of family	Poor*	138	67.65
	Moderate& or Good£	66	32.35

#: Mean ± Standard Deviation (minimum-maximum), *: One or less than one monthly minimum wage, &: Up to 2 monthly minimum wages, £: More than 3 monthly minimum wages

Risk factors considered to affect the IQ level of children with intellectual disability were examined by using Compact, Lasso, Ridged Lasso and Ridge models, all of which are RRMs. These constructed models included the additive linear main effects of the risk factors. In addition, results of the RRMs were evaluated by comparing them with those obtained from multiple linear regression models (CRMs) used for the same purpose. Among models including nine or ten predictors, the Lasso model has the lowest MSE in terms of test sample results (MSE = 95.34), while the compact model has the lowest MSE among the others for the learning sample (MSE = 95.34). In the learning sample results, all full models, including the 23 predictor variables, showed similar success (MSE = 77.30).

Regression coefficients of the RRMs in this study, with different elasticity coefficients in learning and test samples are given in Table 3. Only nine predictors were selected in the Ridge [2.0] model, while the 10 predictors selected for the other models show slight differences. Residence, duration of education, family income, age at onset of speech, age at onset of walking and diagnosis of cerebral palsy, presence of elimination disorders and presence of ADHD show significant levels of contribution in all models. Among these models, the goodness of fit of the Lasso model including 10 predictors was obtained in both the learning sample (AIC = 930.48, AICc = 931.85, BIC = 967.04) and the test sample (AIC = 982.28, AICc = 988.94, BIC = 1062.03). According to degree of importance, the significant predictors included in the Lasso model are the diagnosis of cerebral palsy, age at onset of speech, duration of education, age at onset of walking, presence of elimination disorders, presence of ADHD, family income, number of siblings, residence and age, respectively.

Table 3: **Results of regularized regression models**

	LEARNING				TEST			
	Compact	Lasso	Ridged Lasso	Ridge	Compac t	Lasso	Ridged Lasso	Ridge
Non-zero count*	***10***	***10***	***10***	***9***	***10***	***10***	***10***	***9***
Characteristics								
Constant	68.17	62.85	62.88	53.65	67.29	62.02	62.01	53.65
Age		-0.04	-0.04			-0.02	-0.02	
Gender								
Residence	-0.47	-0.52	-0.52	-0.05	-0.10	-0.43	-0.43	-0.05
Number of siblings	-0.75	-0.28	-0.29		-0.76	-0.24	-0.24	
Number of children								
Primary caretaker								
Family history of ID								
Years of education	0.77	0.66	0.63	0.01	0.77	0.61	0.63	0.01
Special education								
Education level of mother								
Education level of father	-2.32				-2.35			
Reading level								
Writing level				0.05				0.05
Mathematics level								
Income of family	3.83	2.01	2.01	0.05	3.95	2.01	2.01	0.05
Mode of delivery								
Diseases in infancy								
Age at onset of speech	-1.73	-1.40	-1.41	-0.01	-1.73	-1.35	-1.36	-0.01
Age at onset of walking	-1.09	-0.91	-0.91	-0.01	-1.09	-0.91	-0.91	-0.01
Cerebral palsy	-17.94	-15.46	-15.51	-0.06	-18.00	-15.43	-15.22	-0.06
ADHD	-1.66	-1.12	-1.12	-0.03	-1.66	-1.05	-1.05	-0.03
Behavioral disorders								
Elimination disorders	0.52	0.40	0.42	0.01	0.52	0.40	0.40	0.01

*: Number of predictors in model, ID: Intellectual disability, ADHD: Attention-Deficit Hyperactivity Disorder, Elasticity coefficient: [0.0] for compact; [1.0] for Lasso; [1.1] for Ridged Lasso; [2.0] for Ridge

Table 4: **Results of multiple linear regression model**

	Unstandardized Coefficients		Standardized Coefficients		
Characteristics	**Beta**	**SE**	**Beta**	**t**	**p**
Constant	70.76	10.61		6.67	**<0.001***
Age	-0.27	0.35	-0.08	-0.78	0.437
Gender	-0.17	1.44	-0.01	-0.12	0.904
Residence	-1.32	0.93	-0.11	-1.42	0.159
Number of siblings	-0.62	0.68	-0.10	-0.91	0.364
Number of children	-0.15	0.72	-0.02	-0.21	0.833
Primary caretaker	1.39	2.30	0.05	0.61	0.544
Family history of ID	0.87	0.75	0.09	1.16	0.249
Duration of education	0.34	0.42	0.08	0.82	0.416
Special education	-0.50	1.05	-0.04	-0.48	0.632
Education level of mother	-0.97	2.17	-0.04	-0.45	0.657
Education level of father	-2.37	2.10	-0.12	-1.13	0.262
Reading level	-0.87	1.66	-0.07	-0.53	0.601
Writing level	2.66	1.97	0.18	1.35	0.178
Mathematics level	-3.73	3.44	-0.09	-1.09	0.280
Income of family	4.95	1.93	0.23	2.57	**0.011***
Mode of delivery	-0.22	0.68	-0.03	-0.32	0.750
Diseases of infancy	-0.06	0.20	-0.02	-0.30	0.763
Age at onset of speech	-1.63	0.50	-0.26	-3.23	**0.002***
Age at onset of walking	-0.97	0.62	-0.13	-1.58	0.117
Cerebral palsy	-1.47	0.74	-0.15	-1.98	**0.049***
ADHD	1.50	2.21	0.05	0.68	0.497
Behavioral disorders	0.40	0.26	0.11	1.53	0.129

SE: Standard error, ID: Intellectual disability, ADHD: Attention-Deficit Hyperactivity Disorder,*: Significant

A multiple linear regression model was created. The R^2 value was determined as 34.6% and this coefficient was found to be statistically significant ($p < 0.001$) when all 23 predictors of each effect examined were included in the model. When compared with the RRM including the same number of predictors, the R^2 value was approximately 9% lower than all others and the error of the model appeared to be slightly larger (MSE = 77.67). The results of the CRM are collectively given in Table 4. Among the 23 predictors, only three predictors – age at onset of speech, family income, and diagnosis of cerebral palsy – were statistically significant in affecting the IQ score ($p < 0.05$). When CRA was applied to the 10 predictors in the Lasso model, the determination coefficient was calculated as $R^2 = 25.5\%$ and the standard error was 76.11.

Discussion

In this study, the familial, personal and educational factors considered to affect the IQ levels of children and adolescents with intellectual disability were investigated by using modern regression models. Since the ratio of the number of children to the number of variables was approximately 9:1, such a ratio was not sufficiently large for this study, so interaction terms were not included in the model. In practice, the inclusion of interaction in the model leads to incorrect prediction of coefficients in such cases. Therefore, the main effects of the predictors were taken into consideration, but the interaction effects were not included in the models examined.

Each modern and conventional regression techniques were applied to the study data and the resulting models were compared according to goodness of fit indices. As a result of this comparison, the optimum model was obtained via the Lasso approach. Out of 60 (23 predictors + 37 dummy predictors), 10 potential predictors with dummy variables were selected for the model. In this model, it was found that cerebral palsy diagnosis, age at onset of speech, education level of the child, age at onset of walking, presence of elimination disorders, presence of ADHD, family income, number of siblings, residence and age were risk factors that have important effects on the IQ level, according to degree of importance, respectively. In this model, it was found that the least effective predictor was age, while the three most important predictors were cerebral palsy diagnosis, age at onset of speech and the education level of the child.

When CRA was applied to the 23 predictors, the model has only three significant predictors such as age at onset of speech, family income and cerebral palsy diagnosis. According to model fit indices such as determination coefficient and standard error, it can be said that the RRMs gave better results than CRM.

A number of studies in the literature have been conducted to investigate the factors related to intellectual status or affecting the IQ levels of children and adolescents with intellectual disability. A review of the literature shows that the risk factors investigated and found to be effective on the IQ level or intellectual status were age at onset of speech (19), education level of the child (20), age at onset of walking (21), ADHD (22-24), family income (20,25-28), number of siblings (28) and residence (25,29-31). Thus, the findings of the present study show similarity with those of the literature. However, when the “Material and Methods” sections of these studies were reviewed, it was observed that in general, the risk factors were determined via the classical univariate approaches like Pearson chi-square and Pearson correlation or via conventional methods like Logistic or Linear regression analyses.

Recent studies investigating the factors affecting the intelligence level using CRAs include those of Camargo-Figuera et al. (28) and Eriksen et al. (32). Camargo-Figuera et al. (28) identified the main early-life predictors of low IQ in children aged six from a middle-income country birth cohort. The study included 3523 children, 594 of whom had low IQs. Children with severe intellectual disability and cerebral palsy were excluded from the study. Predictors affecting IQ level were determined by using multivariable logistic regression analysis. From the 32 potential predictors of this model, they found the significant predictors of IQ included the variables of the child’s gender, parents’ skin color, number of siblings, employment status of mother and father, household income, maternal education, number of persons per room, duration of breastfeeding, head circumference-for-age and height-for-age deficits, parental smoking during pregnancy, and maternal perception of the child’s health. The results of that study in terms of the age group were consistent with the results of the present study for the child's gender, number of siblings, household income, and maternal education risk factors. Eriksen et al. (32) carried out an extensive examination of the factors affecting the intelligence of 5-year-old children in Denmark by using conventional multiple regression methods. In this study, which included 1772 children, the authors created multiple regression models to investigate the factors (28 predictors) affecting IQ within the scope of family background, pregnancy and birth, postnatal influences and postnatal growth. They found that postnatal influences, parental education, maternal IQ, the child’s sex, breastfeeding, birth weight, head circumference, head circumference squared and height were risk factors affecting intelligence level in general. It was observed that the parental education level and child sex predictors affected IQ level, as in the present study, although, in terms of the target population, the age group studied was not compatible.

In this study, the factors affecting the IQ level of children and adolescents with intellectual disability were determined and RRAs and CRA were comparatively examined. This study brings to light the factors affecting the IQ level of children with intellectual disability by using modern regression approaches. As a result, it can be said that this study is a valuable study in psychiatry, clinical psychology, and public health fields. But in future studies, it is recommended that the interactions be investigated by increasing the value of the sampling fraction, which constituted a constraint for the current study.

The modern regression approaches evaluate more factors in comparison with CRAs. Moreover, they do not require the fulfillment of the strict assumptions of CRAs. In addition, these approaches enable the study of missing datasets by using different algorithms during prediction. More information can be obtained by using these approaches compared with other methods (16-18). Furthermore, these approaches are vital in cases of very large datasets or in cases in which the number of predictor variables is greater than the number of observations. Due to the advantages mentioned in this study, it is recommended that the use of modern regression approaches for very large datasets be expanded to include application in the clinical field.

Contribution of Authors
Study design: SC and HA, Data collection: CI, Statistical analysis: SC and HA, Manuscript preparation: SC, HA and CI.

Conflict of interest
The authors declare that they have no competing interests.

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