Classification of Developmental Language Disorders (DLD) - An Exploratory Study

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Abstract

Developmental Language Disorders (DLDs) pose a great diagnostic challenge to the practicing speech language pathologists in view of the complexities and variability in their manifestations. This is more so in a country like India where multi-lingual and multi-cultural factors influence the acquisition of speech and language in a child. Most of the children are exposed to a minimum of two languages during their preschool and early school years. The diagnostic process is further complicated by the non-availability of standardized language assessment tools in the Indian languages. The present study aimed at developing **C**hecklist for the **A**ssessment of **L**anguage and **B**ehavior (CALB) that would help in classification of children with DLDs, based on literature and case file information with respect to history of onset and development of language disorder, language comprehension, expression and behaviors associated with DLDs. CALB clearly differentiated 7 groups of children with DLD. Further, the classification of DLDs on the basis of Artificial Neural Network and Discriminant analysis is also discussed.

Key words: Developmental Language Disorders (DLDs), Artificial Neural network, Discriminant Analysis

Communication using language is a complex process requiring years of exposure and practice to master the skills. It involves both the understanding and expression of various linguistic parameters including phonology, morphology, semantics, syntax and pragmatics at various levels of complexities. Children who are unable to communicate effectively through language or to use language as a basis for learning are known as children with Developmental Language Disorders (DLD's). Cantwell and Baker (1987) define DLD as "a disturbance or delay in language acquisition that is unexplained by general mental retardation, hearing impairment, neurological impairments or physical abnormalities".

Children with DLDs are a heterogeneous population varying widely with respect to the etiological aspects and various linguistic and nonlinguistic characteristics. The estimates of the prevalence of DLDs vary widely ranging from 10% for two year olds (Rescorla, 1989) to approximately 1% for older children (Enderby & Davies, 1989). Developmental disorders of language in children may manifest in different degrees of severity across different modalities. Therefore, it is necessary to carry out a comprehensive evaluation before classification of these conditions. Classification or sub-typing of children with DLDs facilitate better communication of information among the members of the professional team, promotes further understanding of the nature of these disorders for academic and research purposes, helps to develop more effective assessment and intervention strategies.

Classification of language disorders in children has always posed many challenges. The causative categories are not predictably related to language attributes (Bloom & Lahey, 1978). Besides, the heterogeneity within the diagnostic categories with blurred distinctions across categories most often leads to validity and reliability problems.

A number of classifications of DLD have been proposed, of which the most common is the distinction between expressive and receptive disorders (Myklebust, 1983; American Psychiatric Association, 1994). Recent trends in classification have moved away from considering whole population of language-impaired children towards more refined analysisbased divisions within an identifiable clinical entity (Fletcher 1991; Miller 1991). Subsequently, various authors have proposed finer subdivisions in the classification of DLDs as shown in Table-1.

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Author	Types
Aram & Nation, 1975	Repetition strength
	Non-specific formulation-repetition deficit
	Generalized low performance
	Phonologic comprehension-formulation-repetition deficit
	Comprehension deficit
	Formulation-repetition deficit
Bloom & Lahey, 1978	Impairment in form
-	Impairment in content
	Impairment in use
Denckla, 1981	Anomic disorder
	Anomic disorder with repetition deficits
	Dysphonemic sequencing disorder
	Verbal memory disorder
	Mixed language disorder
	Right hemi-syndrome with mixed language disorder
Bishop & Rosenbloom, 1987	Phonology
	Grammar
	Semantic
	Pragmatics
Rapin & Allen, 1988	Disorder of phonological decoding
	Disorder of phonological encoding
	Disorder of morphological-syntactic decoding &
	encoding
	Disorder of higher level processing
American Psychiatric	Expressive language disorder
Association, DSM IV, 1994	Mixed expressive-receptive language disorder
	Phonologic disorder
Korkman & Hakkinen-Rihu, 1994	Specific dyspraxic subtype
	Specific comprehension subtype
	Specific dysnomia subtype
	Global subtype

Table 1: Classification of DLD's

Most of these classification systems are based on various language tests and detailed assessment of children with DLDs. However, this procedure is very time consuming and is not feasible in routine clinical practice. Further, in the Indian context with its multilingual and multicultural backgrounds, this becomes even more difficult because of the non-availability of standardized tests in different languages covering all aspects of language behavior. Also, most children are exposed to more than one language during the pre-school years, which makes formal assessment of language functions all the more complex. Therefore, there is a dire need for an easy and quick evaluation procedure incorporating the major characteristic features for the diagnosis and classification of children with DLDs. The main objectives of the present study, therefore, are:

- 1. To identify the essential language/linguistic and other behavioral characteristics in children with DLD's.
- 2. To develop a checklist for the quick screening and diagnosis of children with DLDs.
- 3. To classify DLDs using Discriminant Analysis and Artificial Neural Network (ANN), a computer software program that recognizes patterns.

ANN has been successfully employed to classify childhood fluency disorders (Geetha, Prathibha, Ashok, & Ravindra, 2000). Therefore, the present study also attempts to classify children with DLDs with the help of ANN program. Further, discriminant analysis was also employed to identify the crucial variables to facilitate classification of DLD's.

Method

A. Development of tool: 100 case files of children with childhood language disorders were reviewed to analyze the patterns of language and other behavioral characteristic features and the types of DLDs. As the information obtained from the survey of files appeared inadequate to draw any conclusions, a checklist was prepared (CALB) for the assessment of children with different language disorders (see Appendix). The checklist was prepared on the basis of a detailed literature search.

The checklist comprised of:

- 12 items pertaining the history, onset and development of the problem to rule out other associated conditions
- 10 items pertaining to language comprehension including verbal, gestural and reading comprehension and in terms of phonology, syntax, and semantics.
- 10 items pertaining to expression of language including, in addition to those listed under comprehension, repetition skills, pragmatics and writing skills.
- 12 items pertaining to behavioral characteristics six items each for abnormal linguistic and non-linguistic behaviors.

This checklist (CALB) served as a tool for assessing the children with DLDs

B. Participants: 30 children diagnosed as developmental language disorders were taken as subjects for the study. There were 21 male and 9 female children and their age ranged from 3 years to 12 years. There was a positive family history of language problems in 4 (13%) of the training subjects. Four of the children in this group were ambidextrous and one was left-handed. A significant proportion of these children, that is more than 60% were reported to have inadequate language exposure or exposure to more than one language. Further, four new children were selected for checking the prediction of ANN based on their scores obtained on the checklist. None of the children in the training group or those in the prediction group had any significant cognitive, sensory and neuro-motor disabilities.

C. Procedure: The language and related behaviors in the CALB were subjectively rated on a 5- point scale to obtain scores for language comprehension, expression and associated abnormal linguistic and nonlinguistic behaviors. 30 children diagnosed as DLD were assessed using the checklist by the undergraduate and graduate student clinicians handling them, after a minimum of five therapy sessions. This was cross-checked by the two investigators of the present study. The data thus obtained for each child was compared across participants and across different types of DLDs. The data obtained from the 30 children with DLDs based on the checklist was used for training ANN and the data on four new children between 3-4 years was used for prediction.

D. Reliability: Reliability was checked only for intra-subject ratings. Three children selected on a random basis were re-rated on the CALB by the clinicians who had rated them earlier. The intra-rater reliability was 73%. Variability and developmental trends in language and behavior patterns with age did not seem to affect the intra-rater reliability despite the subjectivity of the procedure. Further, most of these children were in the language therapy program which could have resulted in improved ratings subsequently. Inter-tester reliability was not verified as the criteria for rating (handling the child for a minimum of 5 sessions for language therapy) could not be met.

Results and Discussion

A Multiplayer-Perceptron classifier was used for the classification of DLD children. It has wide practical application for pattern recognition and is the most appropriate when binary representations are possible. This kind of network has input, output and hidden layers with variable number of nodes in the hidden layers (Fig.!). ANN is a machine designed to model the way in which the brain performs a particular task or function of interest by using electronic components or simulated in software on a digital computer. It resembles the brain in two respects: Knowledge is acquired by the network through a learning process, and inter-neuron connection strength, known as weights are used to store knowledge. That is, ANNs are biologically inspired networks having the apparent ability to imitate the brain's activity to make decisions and draw conclusions when presented with complex and noisy information (Haykin, 1995). ANN derives its computing power through its massively parallel distributed structure and its ability to learn and generalize, by which it means that it produces reasonable outputs for inputs not encountered during training (learning).



Figure1: Structure of ANN

Empirical classification techniques such as cluster analysis provide methods for grouping individuals who show similar pattern or response on a given set of variables. However, they do not ensure that they (the clusters) are psychologically or educationally meaningful or predictive.

In the present study 32 variables based on the scores for language comprehension (10), expression (10), behavior - nonlinguistic (6) and behavior - linguistic (6) were used as input for training the ANN. Based on these variables, seven classes or groups of children diagnosed as DLD were differentiated. The scores obtained on these 32 variables for the 30 children were normalized or decoded to get scores within zero and one (relative scaling of numbers between maximum and minimum to be mapped to numbers between 0 and 1).

The data obtained for the 30 children with DLD on 32 variables were used to train the ANN. For the classification purpose a Multiplayer Perceptron was adopted with three binary output units (000, 001, 110) representing seven groups. After training ANN with this data for one, two and three hidden layers, with 3-10 units in the hidden layers, output was generated for the 4 new children with DLD for predicting the classification.

Although the training sample and the sample for the output generation were highly inadequate (larger the training sample for the ANN better will be the prediction), there was 50% prediction accuracy for classification using the ANN. This was achieved using one hidden layer with seven nodes as well as two hidden layers with three nodes. Improving the training sample could have enhanced the predictive accuracy of the ANN. This is especially important in view of the large number of variables used for the prediction. Further, all types of DLDs were not incorporated in the training sample and only two types were used for the prediction. Due to the problems in getting adequate number of children with DLDs this could not be done.

As frequently reported by the researchers, most language-impaired children do not fit neatly into one of the descriptions. According to Rapin and Allen (1987), edges of the subtypes are not sharply delineated and that as the child develops, he/she may change from one syndrome to the other. For this claim to be substantiated there would have to be many more finely constructed syndromes than are currently available. Bishop and Rosenbloom (1987) prefer the term 'disorder' to syndrome for this condition because according to them a loosely associated set of behaviors relating to language use and content describe the condition (Semantic-Pragmatic syndrome), which shade into autism at one extreme and normality at the other.

Discriminant analysis

ANN analysis revealed that although the training sample was limited and the sample used for prediction did not represent all the groups taken in the training sample, it is possible to classify the DLD children into subgroups based on the variables selected in the study. Canonical Discriminant Analysis was used in order to check for the classification functions and the variables crucial for these groupings.

Functions	Wilkes'	Chi-	Df	Sig.	Eigen	% of	Cumulative	Canonical
	Lambda	Square		_	Value	variance	%	correlation
1	.000	243.685	132	.000	418.66	84.4	84.4	.999
2	.000	156.113	105	.001	53.51	10.8	95.2	.991
3	.001	98.136	80	.082	14.66	3.0	98.1	.968
4	.018	58.244	57	.429	4.84	1.0	99.1	.910
5	.105	32.660	36	.628	3.15	.6	99.7	.871
6	.436	12,032	17	.798	1.29	.3	100.0	.751

Table-2: Wilkes' Lambda, Chi-square, Eigen values, % of variance, cumulative % and canonical correlations for the six functions

Table-2 gives the Wilke's Lambda, Chi square, Eigen values, percent of variance and the canonical correlations for the 6 functions that were identified in the analysis. Wilke's Lambda is a multi-variable measure of group differences over several discriminating variables. Although 6 functions were identified, first three functions accounted for 98% of variance and highly significant. The Eigen values, which are crucial for identifying the discriminant functions show that the first three functions have very high values compared to the rest. The canonical correlations aid in judging the importance of discriminant functions along with the relationship between the functions and the group variables.

	Functions							
	1	2	3	4	5	6		
CAV	-3.186	-2.881	-3.768	-1.023	547	.174		
CG	.288	.186	.390	-1.905	.629	2.093		
CR	-2.561	606	3.817	.827	1.501	137		
CAP	-3.113	-1.532	332	.347	.737	657		
CVP	-5.312	2.394	1.372	2.711	.667	562		
CPAM	12.715	2.075	3.259	.539	835	722		
CSYN	-4.259	3.861	-2.571	-2.452	-1.530	1.906		
CSEM	10.382	472	1.642	.972	.557	742		
CPROS	.973	1.852	-2.126	318	443	1.205		
COVER	-4.554	-1.955	792	.220	045	.466		
EPP	.774	2.422	1.857	1.148	1.338	1.611		
EARTI	-7.041	-1.037	-4.430	438	328	-1.045		
EPS	-6.108	2.236	2.290	-1.689	.143	.689		
EVF	-11.244	-1.843	-1.653	-2.444	026	1.651		
EVOC	11.073	1.002	1.173	-2.252	.318	-1.386		
ENAM	11.687	264	5.023	6.431	.136	-2.047		
EPRA	-7.099	-1.512	-2.375	069	-1.340	439		
EREP	-4.193	431	1.681	1.598	.667	987		
ECOPY	11.194	.100	3.825	.809	1.994	257		
ESPELL	-3.659	-2.446	-4.075	-2.091	937	.804		
BNLAC	7.869	-1.045	2.202	3.321	1.146	159		
BNLGB	6.486	.982	2.146	-1.510	.549	1.096		

Table 3: Standardized Canonical Discriminant Function Coefficients

BL-Behavior Linguistic; E-Echolalia; ; P-Perseveration; APR-Apraxia; NEO-Neologisms; M-Mutism; TS-Telegraphic Speech; BNL- Behavior Non-Linguistic; IT-Incoherent Thought process or behavior; HA-Hypersensitive to Auditory stimuli; IS-Insistence on Sameness; IB-Inappropriate Behavior;



Figure 2: Grouping of Canonical discriminant variables

Table 3 and Figure 2 shows the groupings of the children with DLDs with respect to Function 1 and Function 2. Although raw data seemed to indicate wide variability in the spread of scores across all the variables and across groups, it was interesting to see clear separation of the seven groups, without any overlap. Function 1 separates the groups on the linguistic behavior dimension with learning disabled children on the negative end to those with associated problems such as tic disorder at the positive end, those with phonetic disorder and developmental dysphasia lying in the middle. Function 2 separates the groups across nonlinguistic behavior dimension with delayed language at the negative end to autism at the positive end of the continuum.

Functions	Variables								
1	BLTS	BLNEO	BLAPR	BNLIT	BNLHA	BNLIS	BLE	BLP	
	.532	.319	.199	.145	113	.076	069	054	
2	BNLIB	BLP	BNLIS	BNLHA	BLTS	EARTI	CSYN	CG	
	.296	.237	.198	.160	.125	.106	.081	073	
3	BLP	BLTS	BNLIB	BNLIS	BLAPR	BNLIT	EPS	EPRA	
	375	.370	368	260	217	.233	.127	.101	
4	BLAPR	EPRA	BNLIB	CPROS	BLP	BLTS	ENAM	BLMUTE	
	.338	.244	368	.233	.221	202	.192	155	
5	CPAM	BNLIT	CAV	CAP	CSYN	EPRA	ESEM	BNLGB	
	406	.396	359	552	342	333	333	.299	
6	BNLIS	BLAPR	BNLIB	BLNEO	ESPELL	BLE	CPRO	EPS	
	317	.299	279	.239	.204	200	194	180	

Table 4: Structure matrix

BL-Behavior Linguistic; E-Echolalia; ; P-Perseveration; APR-Apraxia; NEO-Neologisms; M-Mutism; TS-Telegraphic Speech; BNL- Behavior Non-Linguistic; IT-Incoherent Thought process or behavior; HA-Hypersensitive to Auditory stimuli; IS-Insistence on Sameness; IB-Inappropriate Behavior;

Standardized discriminant function coefficients computed provide a measure of the relative contribution of the associated variable to that function. Table 4 provides the discriminant function coefficients for each of the functions. The signs indicate whether they are making a positive or negative contribution on a continuum. In the structure matrix variables are ordered by size of correlation within the function. From this variables having high correlations were separated for each function, irrespective of their signs (Table 4) and each function was named according to the variables contributing maximum for the separation of discriminant functions, after separating the common variables across two functions.

Accordingly, the six functions were named as:

1 - Linguistic behavior dimension

2 - Non-linguistic behavior dimension

3 - Phonological dimension

- 4 Expressive dimension
- 5 Comprehension dimension and
- 6 Reading and spelling dimension.

As noted earlier, the sample of children with DLD taken for the study did not represent all varieties that are available and those that are identifiable as per the currently available tests or tools. To account for these it is proposed to classify them based on the language and behavioral (both linguistic and nonlinguistic) characteristics that are possible. This would include:

DisordersI.Phonological disorderII.Syntactic disorderIII.Semantic disorderIV.Pragmatic disorderV.Behavioral disorder- Linguistic/Nonliguistic

VI. Mixed disorder

Modalities affected Comprehension Expression Verbal Gestural Reading Writing Spelling

Summary and Conclusion

The study aimed at classification of children with DLDs based on a checklist developed for the purpose – Checklist for the Assessment of Language and Behavior (CALB). It was possible to classify 7 groups of DLD children (N=30) without overlap using Canonical Discriminant Function Analysis. The results of the analysis clearly indicate that CALB may be used for quick screening of children with language disorders and to classify them based on the scores obtained. A new approach for the classification of DLD children incorporating various language comprehension, expression and behavioral (both linguistic and nonlinguistic) characteristics has been proposed. ANN, a computer based neural network program was also adopted to check for the efficacy of the program in predicting the classification. Though the training sample and the sample for predicting the accuracy of classification was very small, it could yield more than 50% accuracy in the ANN prediction.

Improving the training sample and inclusion of all varieties of DLD children would definitely provide better prediction and ANN could be used effectively in sub-grouping these children.

The study has great implication for the identification/classification of children with developmental language disorders, which in turn will facilitate better management options. This is especially so in the Indian context with its multi-lingual and multi-cultural background. However, this needs to be tried on a larger population of DLDs including all possible varieties or types of cases.

Limitations of the study

- Assessment of language and behaviors were based on subjective ratings by the student clinicians
- Limited number of subjects used for both training groups
- Limited variety of DLD groups
- Limited number and variety of subjects for prediction group

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APPENDIX CHECKLIST FOR ASSESSMENT OF LANGUAGE AND BEHAVIOR (CALB)

Cas PD:	e name:	No: Clinician:	Age: No. of	sessions	::	Sex: Date:	
I. B	rief h/o the problem:						
2. F 3. H 5. E 6. N 7. H 9. H 10. 11. M 12. S	Diset: Family h/o speech/lang. proble H/o brain damage: Handedness: Exposure to language: No. of languages: H/o any neuro-motor disorder: H/o any sensory impairment: H/o any cognitive impairment: H/o any other problem: Motor development: Speech mechanism: Se rate the child's speech, la [1 – Very poor 2 – Poor	0 – No 0 – Right 0 – Adequate 0 – Mon 0 – No 0 – No 0 – No 0 – No 0 – Normal 0 - Normal	1 – 1 – 0.5 – Ambilater 1 – Inadequa olingual 0.5 – E 1 – Yes (spe 1 – Yes (spe 1 – Yes (spe 1 – Yes (spe 0.5 – delaye 1 – Defective	Yes (spe Yes al 1 – ate Bilingual acify) acify) acify) d (specify) d (specify)	Left 1 – 1 – Dev) cale as:	Multiling	ual
II. Co	omprehension:		1	2	3	4	5
1. 2. 3. 4. 5. 6. 7. 8. 9. 10.	Auditory verbal comprehen Gestural comprehension Reading comprehension Auditory perception Visual perception Phonological awareness a Syntax Semantics Prosodic variations Overall comprehension ab	and memory					
III. Expr	ession:		1	2	3	4	5
1. 2. 3. 4. 5. 6. 7. 8. 9.	Phonological processes Phonetic expression (articulat Phonological sequencing Syntactic expression Verbal fluency Semantic expression-Vocabu Naming Pragmatic skills Repetition Writing skills - Copying Spelling				-		
	avioral/ Social skills:	t. A Vany fraguant	5 Alwoval				
A. Non- 1. P 2. C 3. Ir 4. H 5. Ir	Nil; 2- Occasional; 3- Frequen linguistic: Poor attention and concentratio General behavioral irregularities happropriate behaviors lypersensitivity to sensory stim histing on sameness hicoherent thought processes of	n s} (Please specify } abnormalities if nuli	1	2	3	4	5
1. Ec 2. Pe 3. Ap 4. Ne 5. M	guistic: cholalia erseveration praxic errors eologisms utism elegraphic speech						