8-5-2011

Identifying Key Success Factors of Vocational Rehabilitation Services Program for People with Disabilities: A Multi-Level Analysis Approach

Yong Seog Kim
Utah State University, yong.kim@usu.edu

Identifying Key Success Factors of Vocational Rehabilitation Services Program for People with Disabilities: A Multi-Level Analysis Approach

Yong Seog Kim
Utah State University
yong.kim@usu.edu

ABSTRACT

This study proposes a multi-level approach to identify both superficial and latent relationships among variables in the data set obtained from a vocational rehabilitation (VR) services program of people with significant disabilities. In our study, classification models are first used to extract the superficial relationships between dependent and independent variables at the first level, and association rule mining algorithms are employed to extract additional sets of interesting associative relationships among variables at the second level. Finally, nonlinear nonparametric canonical correlation analysis (NLCCA) along with clustering algorithm is employed to identify latent nonlinear relationships. Experimental outputs validate the usefulness of the proposed approach.

Keywords

Multi-level analysis approach, vocational rehabilitation services, classification, association rule, clustering, NLCCA

INTRODUCTION

The objective of this research is to identify key success factors of a vocational rehabilitation (VR) services program for people with significant disabilities. While Congress, U.S. Department of Education, and state and local governments have supported VR services for people with disabilities, only few U.S. federal laws regulate business practices for people with disabilities. The examples of such regulations include Americans with Disabilities Act (ADA) of 1990, Section 508 of the Rehabilitation Act 29 U.S.C. § 794(d), and Section 255 of the Telecommunications Act of 1996. These laws and regulations directly or indirectly enforce Web sites and information (and information technology) from the federal government to be accessible to people with disabilities. During the past decades, many U.S. states have tried to make Web sites and other applications such as newsgroups, chat, and e-mail more accessible based on guidelines initiated by the W3C and the Internet Societal Task Force.

This study takes a multi-level analysis approach that combines three sets of data analysis techniques to identify both external and internal factors that affect the success of VR programs. Note that one of the most popular VR programs for people with disabilities is to provide an on-site job training including IT trainings and other ongoing supports. From the perspective of practitioners such as education program designers and policy developers, developing successful VR programs and providing other supports to people with significant disabilities require comprehensive understanding personal characteristics of VR trainees, trainers, and training materials and curricula. For example, noting that not all trainees can find and keep their jobs, VR program designers first like to know through predictive classification models which VR trainees are most likely to secure a job after completing a VR service program. Then, they like to profile VR trainees who are most likely (or unlikely) succeed in terms of personal and/or VR program related descriptive information using association rule models to complete the black box types of predictive classification models. Finally, they can use identified latent self-perceptions and physical and psychological hindrance factors that may negatively affect the outcomes of VR services program to develop a training session of VR trainers so that they can better educate VR trainees and maximize the outcomes of VR services program.

The remainder of this paper is organized as follows. A brief introduction to our research model and VR data set is first presented. Then the predictive performance of single classifiers and ensemble classifiers are compared and discussed. Next we present association rule algorithms and interpret outputs. Then, managerial implications and the relationships among multiple sets of key variables based on NLCCA and clustering are presented and discussed.

RESEARCH METHODOLOGY AND DATA DESCRIPTION

Research Methodology

This study employs a multi-level approach to fully identify superficial and latent relationships among variables in VR data sets. The main task in the first level analysis is classification, identifying the relationships between dependent and independent variables for prediction purpose. We consider the identified relationships between dependent and independent variables "superficial" because in-depth understanding on possibly complex and hidden relationships among variables is not required as long as the identified relationships are useful for predicting the value of the dependent variable. The classification task considered in this study is to accurately predict and profile VR trainees who are most likely to find and keep a job after completing a VR service program. Then the resulting predictive model can be used by developers and administrators of VR training programs to estimate the success rate in advance for a new pool of VR trainees and pay more attention to trainees during the training program who are less likely to find and keep jobs. Further, program administrators may consider offering different VR service programs in terms of program contents and length depending on VR training applicants' likelihood of finding a job. Any predictive classifiers may be used and evaluated in terms of predictive accuracy, computational complexity, and performance robustness.

At the second level, managerial insights that can be extracted from the predictive and other descriptive models become more important, assuming that the most predictive model is already obtained at the first level. For example, administrative managers, VR program developers, and state and federal officers may want to know what factors (i.e., VR program related or demographic related) are influential on post VR employment status. In addition, a new analysis at the second level can provide important (associative) relationships among independent variables. With additional relationships and insights, VR service program managers and developers may consider changing or controlling a certain set of instruments toward better VR outcomes. For this purpose, an association algorithm is introduced and applied.

Finally, at the third level, the main objective is to identify the relationships between psychological and societal characteristics of VR trainees and external outcomes of VR training. In particular, we like to identify the latent relationships between self-perception (e.g., self-confidence and self-esteem) and physical and psychological hindrance factors, which in turn affect social activities and presumably the outcomes of VR services program. To discover these latent relationships, we segment participants based on their perceptions of themselves (i.e., self-esteem and self-confidence level, and the subjective weights they assign to physical and psychological hindrance factors on their social activities) and relate the segmentation characteristics to personal factors (i.e., gender and marriage status) and disability-related factors (i.e., disability type and severity). Then, NLCCA is conducted with three sets variables: a seven-category segmentation variable from clustering analysis, disability characteristics (disability type and severity), and personal variables (gender and marriage status). NLCCA is a form of canonical correlation analysis in which categorical variables are optimally scaled as an integral component in finding linear combinations of variables with the highest correlations between them.

Data Description

We started with the data set from the Longitudinal Study of the Vocational Rehabilitation Services Program (LSVRSP). This data set is publicly available at http://www.ilr.cornell.edu/edi/lsvrsp/ and contains a total of 8818 records with 951 input variables from eight data sets. The input variables we selected for our study included demographic information (e.g., age, gender, race, marriage status), disability related variables (e.g., type and severity), respondents' perceived importance of physical and psychological hindrance factors, self-esteem and self-confidence on their social activities, and post VR employment status. We also identified primary eight disability types based on Cornell's recoding: orthopedic including amputation, mental illness, non-orthopedic physical, mental retardation, hearing, vision impairment, substance abuse, and traumatic brain injury. In fact, one more disability type, learning disability, was identified but there was no matching record after we removed all records with missing values. The final data set includes 1895 records with employment outcome and 1200 records without employment outcome. Further information regarding the LSVRSP including data dictionaries and user's guide can be found at http://www.LSVRSP.org.

LEVEL 1 ANALYSIS: CLASSIFICATION WITH SINGLE AND ENSEMBLE CLASSIFIERS

We first tested whether or not many well known data mining algorithms can successfully predict post VR employment status based on trainees' self-esteem, self-confidence, and physical and psychological hindrance factors on their social activities. Using Weka, a free data mining tool (http://www.cs.waikato.ac.nz/ml/weka/), four well known classifiers—ZeroR, Logistic regression, artificial neural network (ANN), and decision tree algorithm (C4.5)—were implemented. The ZeroR classifier in this study was included to serve as a basis algorithm because of its simple classification rule, predicting all observations as points in the majority class. The Logistic regression is one of the most popular statistical classifiers. The ANNs is a nonlinear classifier that has been known to be robust and accurate, but it is difficult to understand classification rules from ANNs because of its black-box algorithm characteristics and structural complexities with many subjective parameter settings. Unlike ANNs, the C4.5 is relatively free from subjective parameter setting, and it is faster and provides much more interpretable decision rules while providing a comparable performance with ANNs. In our implementations of these algorithms, we used all default settings in Weka for easy replications of our results except the number of hidden layers (which was set to three to replicate the most popular ANN structure) in an ANN. To fairly evaluate these algorithms, we took a 10-fold cross validation scheme in which the entire data set is divided into 10 equal size blocks and each block is in turn used as a test set while the classifier is built on the remaining blocks. We summarized the performance of these classifiers in Table 1.

The predictive accuracy of ZeroR was expected to be 61.21% because records with the majority class, trainees with a job after VR program, consist of 61.21% of the data set (1895 trainees out of a total 3096 trainees). The accuracy of ANN model (80.07%) was acceptable considering the fact that we did not try to find the best performing parameter values such as the number of epoch (=training time), learning rate, momentum rate, and most of all, the number of hidden layers. The accuracy of a Logistic regression model (82.39%) was significantly better than ZeroR, but only slightly better than ANN. The best performance was recorded by C4.5 with an 83.49% of accuracy. We also observed that the ZeroR was the fastest, followed by C4.5, Logistic regression, and ANN. Based on predictive accuracy, speed, and easy interpretability, C4.5 was chosen to be the best (we will discuss in detail about the interpretation of C4.5 tree model in the following sections).

Table 1. Summary of Single Classifier Performance

Classifiers	ZeroR	Logistic	ANN	C4.5
Accuracy	61.21%	82.39%	80.07%	83.49%
Speed	1st Fastest	3rd Fastest	4nd Fastest	2nd Fastest
Interpretability	Good	Good	Bad	Good

In addition to single classifiers, ensemble classifiers (or meta-classifiers) that combine multiple classifiers were also tested to see if the performance of a single classifier can be improved. Bagging (Breiman, 1996) and Boosting (Freund and Schapire, 1996) are the most popular methods for creating a meta-classifier. Since C4.5 was the best single classifier in afore-mentioned experiment, we combined 25 C4.5 tree classifiers to form the AdaBoost and Bagging ensembles, respectively. To our surprise, the performance of the AdaBoost and Bagging models (78.75% and 83.46%) was not significantly better than that of single C4.5 tree, while they took almost 25 times longer to build an ensemble prediction model than a single C4.5 tree. Overall, highly accurate and fast C4.5 classifier can predict who are most likely to secure a job after VR program using only 15 input variables, while associations among these input variables are not fully discovered.

LEVEL 2 ANALYSIS: ASSOCIATION ANALYSIS

A simple introduction to association rule is necessary. Typically, an association rule, Ri, is represented in the form [A => B] where each A and B represents an itemset (e.g., a set of products) in a transaction record where $A \cap B = \emptyset$. For convenience, we refer to A and B as the assumption (or antecedent) and the consequent of the rule, respectively. In addition, we denote D as a set of transactions, while $\|D\|$ and count(A) denotes the number of transactions in D and the number of transactions containing A, respectively. Then, the support and confidence of Ri is defined as count(A)/$\|D\|$ and count($A \cup B$)/$\|D\|$, respectively. Note that the support of Ri measures the prior probability of the antecedent, while the confidence of Ri measures the conditional probability of the consequent (B) given the antecedent (A). Intuitively, the higher the support of the rule the more prevalent the rule is, and the higher the confidence of the rule the more reliable the rule is (Brijs et al., 1999). Ultimately, the main objective of association analysis is to generate all the association rules that have support and confidence greater than the user-specified minimum support and minimum confidence. In particular, descriptive association rules become more useful and provide additional information when too many *if–then* decision rules from the chosen C4.5 decision tree classifier (with 74 leaves and 28 nodes) from the analysis at the first level make it difficult to understand.

In Weka, three different types of association algorithms are available: Apriori (Agrawal and Skirant, 1994), Predictive Apriori (Scheffer, 2005), and Tertius (Flach and Lachiche, 2001). Note that it is not our main goal to compare all these algorithms for prediction accuracy as in (Mazid et al., 2008), but to extract associative relationships among variables in VR data set as many as possible. Note that Apriori and Predictive Apriori are very similar with very comparable predictive power (Mazid et al., 2008), and hence we only present the output of Apriori in Table 2.

Table 2: Output of Apriori association rule

A1. Social=2 1925 ==> C-Soc-Pys=0 C-Soc-See=0 C-Soc-Psy=0 1925
A20. Social=2 Cultural-C=1 1634 ==> C-Soc-Pys=0 C-Soc-See=0 C-Soc-Psy=0 1634
A39. Race=1 Social=2 1925 ==> C-Soc-Pys=0 C-Soc-See=0 C-Soc-Psy=0 1627
A58. Social=2 Social-SMeeting=2 1384 ==> C-Soc-Pys=0 C-Soc-See=0 C-Soc-Psy=0 1384
A191. Social=2 Cultural-C=1 I26=1 1042 ==> C-Soc-Pys=0 C-Soc-See=0 C-Soc-Psy=0 1042
A286. Social=2 PSEVER-C=2 944 ==> C-Soc-Pys=0 C-Soc-See=0 C-Soc-Psy=0 944
A305. Gender=2 Social=2 907 ==> C-Soc-Pys=0 C-Soc-See=0 C-Soc-Psy=0 907
A324. Marriage=5 Social=2 904 ==> C-Soc-Pys=0 C-Soc-See=0 C-Soc-Psy=0 904

The rules shown in Table 2 were subjectively chosen out of 1000 rules that satisfied the minimum support and confidence criteria to present only rules with different implications. Let's take the first rule, A1, which means that trainees who believe their disability does not prevent them from socializing with friends outside (Social = 2) also believe that their physical, sight, and psychological impairments are not critical factors for their social activity (C-Soc-Pys=0, C-Soc-See=0, C-Soc-Psy=0). Note that the numbers in A1 indicate the number of records in VR data set that satisfy the assumption (1925 trainees with Social = 2) and antecedent (1925 trainees with C-Soc-Pys=0, C-Soc-See=0, C-Soc-Psy=0) of A1, respectively. We find that most rules shown in Table 2 include the same antecedent, referring to the trainees who feel their physical, sight, and psychological impairments are not important for their social activity (C-Soc-Pys=0, C-Soc-See=0, C-Soc-Psy=0). According to rules, A20, A39, and A58, these trainees are those who keeps social activities even with their disability (Social = 2), and does not bother with cultural background (A20; Cultural-C=1), or who are Caucasian (A39; Race = 1), or who participated in social meeting for people with disability (A58; Social-SMeeting=2).

Similarly, A191, A286, A305, and A324 also describe trainees who consider physical, sight, and psychological impairments are minor factor for their social activity. These people are who do not bother their social activities because of their disability while they are either who think cultural factor is not very import and secure post VR employment (A191, Social=2, Cultural-C=1, and I26=1); or who are severely, but not most severely, disabled (A286, Social=2 and PSEVER-C=2); or either female or never married trainees who do not bother their social activities because of their disability (R305, Social = 2 and Gender = 2; R324, Marriage = 5 and Social = 2). While classifiers mainly consider the *predictive* relationships between predictors and class variables, association rule algorithms mainly provide *descriptive* relationships among predictors, and hence provide additional insights for VR program administrators and education program developers to better understand trainees with disability or maximize the outcomes of VR service programs.

LEVEL 3 ANALYSIS: CLUSTERING AND NLCCA

Clustering Analysis

In this study, cluster analyses were performed in the space of the four social-activity hindrance and encouragement factors using a K-means clustering algorithm. The first factor, self-esteem, is a social-activity encouragement variable and is measured through aggregating answers from given by interviewees to six questions. We expect that person with higher self-esteem is more inclined to having social activity and hence outcomes of vocational training will be positive. The second factor, self-confidence, is another social-activity encouragement variable and hence is expected to be positively related to social activity and outcomes of vocational training. In particular, strong self-confidence can create positive will power that people with disability overcome many psychological and even physical hindrances to accomplish the goals of activities. Two remaining factors, social-physical and social-psychological factors, reflect respondents' own judgments on how significantly their physical disability and psychological disturbance affects their social activity.

After trying several clustering analyses with between 5 and 10 clusters, we found that K-means with 7 clusters satisfy our subjective criterion, at least 100 records and at most 1000 records in each cluster to draw reliable cluster characteristics. Based on cluster centers, we draw qualitative characteristics of each segment and summarize them in Table 3. One encouraging observation we made is that people with disability in the largest segment (C4, 28.9%) maintain a very high level of self-esteem and self-confidence, and believe that their physical disability and psychological hindrance factors do not significantly affect their social activity. In addition, people in C5 (13.7%) also do not regard their physical disability and psychological factors as a significant factor to limit their social activity. However, people in segment C6 (3.6%) and C2 (13.5%) maintain a low level of self-esteem and self-confidence, and keep limited social activity because of physical and psychological factor originated from their disability. Other people (C1, 9.6%) have a high level of self-esteem and self-confidence, but maintain limited social activity due to their physical and psychological reasons related their disability. Finally, remaining people in C3 and C7 (30.7%) maintain a low level of self-esteem and self-confidence, but actively involved in social activity.

Table 3. Cluster characteristics

Cluster	Social activity hindrance and encouragement factors	Cases	
		N	%
C1	**Very high motivation and very high hindrance:** Maintain very high level of self-esteem and self-confidence. Consider physical and psychological factors significant on their social activity.	298	9.6
C2	**Low motivation and very high hindrance:** Maintain very low level of self-esteem and somewhat low self-confidence. Consider physical and psychological factors significant on their social activity.	417	13.5
C3	**Very low motivation and very low hindrance:** Maintain very low level of self-esteem and self-confidence. Consider physical and psychological factors not significant on social activity.	612	19.8
C4	**Very high motivation and very low hindrance:** Maintain very high level of self-esteem and self-confidence. Consider physical and psychological factors not significant on their social activity.	895	28.9
C5	**Average motivation and very low hindrance:** Maintain a median level of self-esteem and self-confidence. Consider physical and psychological factors not significant on social activity.	424	13.7
C6	**Low motivation and very high hindrance:** Maintain somewhat low level of self-esteem and very low level of self-confidence. Consider physical and psychological factors significant on their social activity.	110	3.6
C7	**Low motivation and very low hindrance:** Maintain very low level of self-esteem and somewhat low self-confidence. Consider physical and psychological factors not significant on social activity.	339	10.9

Nonlinear Canonical Correlation Analysis (NLCCA)

We utilized OVERALS procedure available in categories module of SPSS to conduct NLCCA. In OVERALS, categorical variables are quantified using optimal scaling and treated as numerical variables. For nominal variables, OVERALS creates values for each category while ignoring the order of the categories so that the goodness-of-fit is maximized. For ordinal and interval variables, OVERALS retains the order of the categories while creating values to maximize the goodness-of-fit of a model. OVERALS output includes several measures of goodness-of-fit, component loadings, optimal category scores, and plots including component loadings plots, category centroids plots, and transformation plots. Component loadings in NLCCA and factor loadings in PCA are similar in the sense that they represent correlations between the optimally scaled variables and the canonical variates. Therefore, we can infer how much of the variable was explained by the canonical variates in total by computing the sum of squared loadings, the distance between the origin and the component loadings of a given variable in the orthogonal space of the canonical variates (Ter Braak, 1990).

To explain how strongly the disability-related and personal characteristics affect the level of social activities of people with disabilities, a NLCCA model was specified with three sets variables (shown in Table 4). The first variable set consists of the seven-category segmentation variable based on social activity hindrance and encouragement factors. In our analysis, this variable was considered as ‘‘multiple nominal’’ having different optimal category quantifications for each canonical dimension (i.e., different contribution to the canonical variates). The second set consists of the two disability characteristics (disability type and severity of disability), while two personal demographic variables (gender and marriage status) were assigned to the third set. Each variable in the second and third sets was considered as “single nominal” with a single optimal quantification for all canonical dimensions.

Table 4. Variables in Nonlinear Canonical Correlation Analysis

Set	Variable	Type	Categories	Cases	
				N	%
1	Cluster indexes based on social activity hindrance and encouragement factors	Multiple nominal	Refer to Table 3	Refer to Table 3	
2	Disability type	Single	1= Orthopedic including amputation	876	28.3

		nominal	2=Mental illness	633	20.5
			3=Non-orthopedic physical	586	18.9
			4=Mental retardation	274	8.9
			5=Hearing	273	8.9
			6=Vision impairment	256	8.3
			7=Substance abuse	142	4.6
			8=Traumatic brain injury	55	1.7
	Severity of disability	Single nominal	1=Most Severely Disabled	604	19.5
			2=Severely Disabled	1614	52.1
			3=Not Severely Disabled	877	28.4
3	Gender	Single nominal	1=male	1585	51.2
			2=female	1510	48.8
	Marriage status	Single nominal	1=Married	954	30.8
			2=Widowed	158	5.1
			3=Divorced	508	16.4
			4=Separated	155	5.0
			5=Never Married	1320	42.7
	Race	Single nominal	1=White	2600	84.0
			2=Black	436	14.1
			3=American Indian or Alaskan Native	23	0.7
			4=Asian or Pacific Islander	36	1.2

A two-dimensional NLCCA solution was chosen and the overall fit (=eigenvalues) of this two-dimensional solution in terms of the variance accounted for within each set of variables by each of the two dimensions (canonical variates) is shown in Table 5. Note that the maximum fit value equals the number of dimension, indicating the perfect relationship. The overall fit of our model was 0.893, a sum of two eigenvalues from the first variate (0.528) and the second variate (0.365). Therefore 0.528/0.893=59.1% of the actual relationship among each set of variables is explained by the first dimension. The canonical correlation, a measure of the correlations among the three sets of variables, for each of the canonical variates can be also computed from eigenvalues as follows:

$$\rho_d = \frac{((K \times E_d)-1)}{K-1}$$

where d is the dimension number, K is the number of sets, and E is the eigenvlaue. Using d = 2 and K = 3, we obtained the canonical correlation for each dimension, 0.292 and 0.048 respectively, and hence the first dimension is approximately 6 times more effective than the second at capturing the relationships among the three sets. We also note that, in terms of the variables of sets two and three, the first canonical variate primarily relates disability type to marriage status in set three, while the second variate mainly relates the severity of disability to gender.

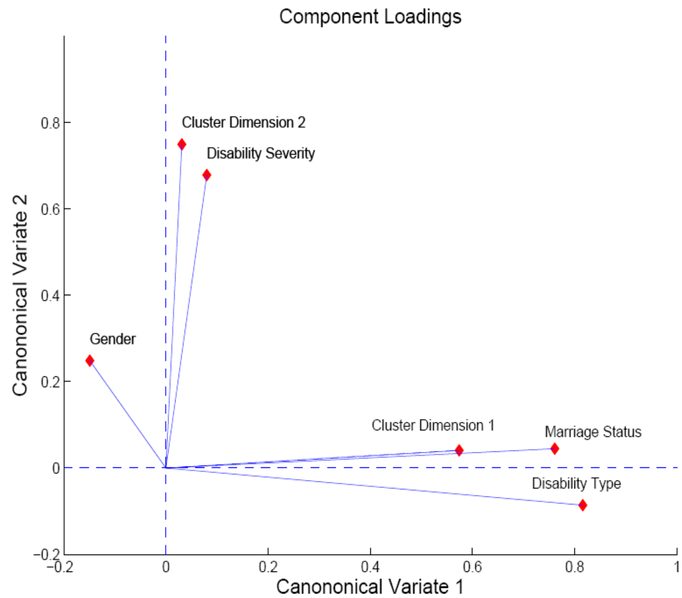

Figure 1. Component loadings

The component loadings of each variable in Figure 1 are measures of the correlations between the optimally scaled variables and the two orthogonal canonical variates. Note that the first dimension is measured along the abscissa and the second along the ordinate. The length of the vector from the origin to the coordinates of each variable indicates the extent to which the variable is explained by the two canonical variates (the square of the length being equal to the percent of variance explained by all the other variables). The segmentation variable has two locations in the canonical space because it is allowed to have a different quantification for each dimension. The scalar (dot) product between any two variable vectors is indicative of the correlation between the two optimally scaled variables (Ter Braak 1990).

The components loadings plot shows that disability type and marriage status are highly related to differences among one of the disability perception segments (that most closely aligned with the first and most powerful canonical dimension), while the severity of disability is correlated with the other less powerful dimension (i.e., the second dimension). Contribution to its explanation of gender is derived almost equally from each of the two canonical deviates variables, although gender is the least well-explained (R^2 = 0.067) by the two canonical variates. Disability type, on the other hand, is the best-explained disability characteristic (R^2 = 0.672) and contributions to its explanation are derived almost entirely from the first canonical deviate.

Figure 2 shows that disability type is almost entirely explained by the first canonical variate. Note that all physical types of disability (e.g., vision, orthopedic, and hearing disability) belong to the negative domain of the first variate, while all mental types of disability (e.g., brain injury, mental retardation, mental illness, non-orthopedic, and substance abuse) are located in the positive domain of the first variate. We also note that people with mental type of disability are aligned with segments (C3, C5, and C7) with a low level of self-esteem and self-confidence. These people typically do not consider their disability a significant hindrance factor of social activity. People with vision disability are located closely to the C1 segment in which many people maintain a high level of self-esteem and self-confidence, but their disability imposes a significant hindrance on their social activity.

Figure 3 shows that the severity of the disability is mainly explained by the second canonical variate. It is interesting to observe that most severe disability is located in the negative domain while severe and non-severe disability is located in the positive domain of the second variate. This insinuates that people with most severe disability (located to close to a segment C4) maintain a high self-esteem and self-confidence, but maintain a low level of physical and psychological hindrance factor. People with non-severe disability are closely located to a segment C3 that shows a low level of self-esteem and self-confidence, and a low level of physical and psychological hindrance factor. We also observe that people with severe (but not most severe) disability are located in a close range to a segment C2 in which people maintain a low level of self-esteem and self-confidence, and suffer from physical and psychological hindrance factor. In short, most people with disabilities believe that their disability does not impose physical and psychological burden on their social activities, but affects their self-esteem and self-confidence. To our surprise, people with non-severe disability maintain a lower level of self-esteem and self-confidence than people with severe disability. We attribute this finding to the fact that people with non-severe disability often lament after comparing their situations to those of people whom they consider normal.

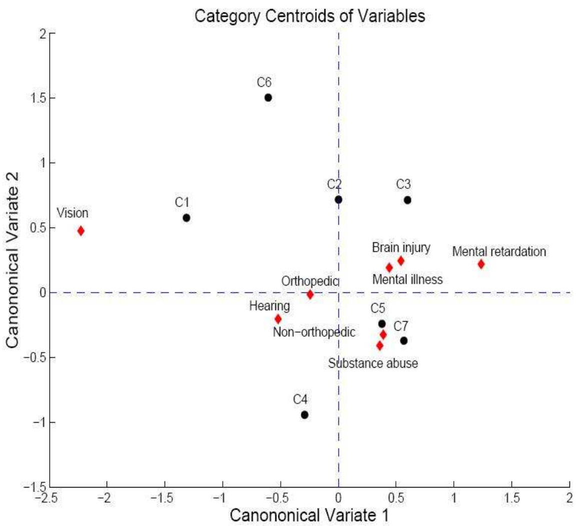

Figure 2. Category centroids for disability type

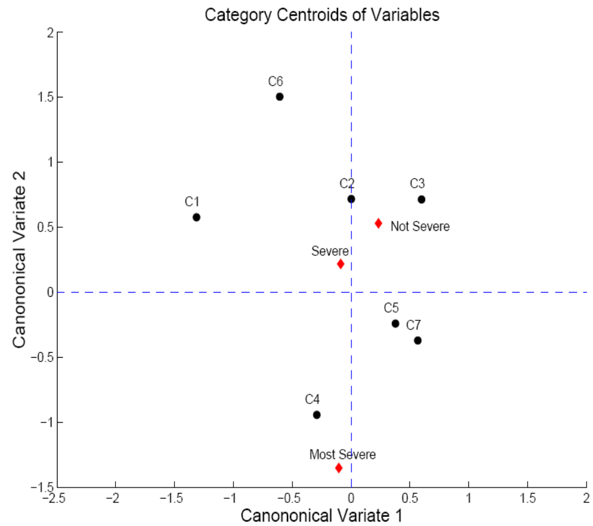

Figure 3. Category centroids for disability severity

CONCLUSION

In this study, we propose a multi-level analysis approach in which the outcomes of multi-level analyses are integrated to identify both external and internal factors that affect the success of VR programs. For this purpose, an accurate decision classifier is calibrated to classify which VR trainees are most likely to secure a job after VR training. Then, VR trainees are further profiled along personal and/or VR program related information using descriptive association rule models to complete predictive classification models, resulting additional insights. Finally, clustering and NLCCA are employed to understand deep psychological and societal characteristics of VR trainees and to analyze the relationships between their internal psychological factors and their social activity. These comprehensive understanding from multi-level analyses can help VR program organizers develop a training session of VR trainers so that they can better educate VR trainees and maximize the outcomes of VR services program by considering the severity of trainees' disability and the level of self-esteem and self-confidence.

As an extension of the current study, we are currently exploring a new NLCCA model that includes the post VR employment status variable itself as another set of variables to explain the relationship between canonical variates and VR employment status variables along with clustering indexes, disability-related variables, personal characteristics, and social cognitive factors. Further, we will draw insights on how we should develop and organize IT and IS training programs to maximize the effectiveness of VR services for trainees with disabilities. This is important to note because if trainees who have job-training (regardless of the fact that they actually have a job after VR training program) maintain much higher self-esteem and self-confidence level, local and state governments may revise their VR programs to reach out more trainees with disabilities to boost their self-esteem and self-confidence, which will lead to a higher quality of life for people with disability.

REFERENCES

1. Agrawal, R. and Srikant, R. (1994). Fast algorithms for mining association rules, Proceedings of the 20th International Conference on Very Large Databases, Santiago, Chile, 487-499.
2. Breiman, L. (1996). Bagging predictors, Machine Learning, 24(2): 123–140.
3. Brijs, T., Swinnen, G., Vanhoof, K., andWets, G. (1999). Using association rules for product assortment decisions: A case study. In Proceedings of 5th Int'l Conf. on Knowledge Discovery & Data Mining (KDD-99), 254–260, New York, NY. ACM Press.
4. Flach, P.A. and Lachiche, N. (2001). Confirmation-Guided Discovery of First-Order Rules with Tertius, Machine Learning, 42(1-2), 61-95.

5. Freund, Y. and Schapire, R. (1996). Experiments with a new boosting algorithm, Proceedings of the 13th Int'l Conf. on Machine Learning, 148–156.
6. Jain, A., Murty, M., & Flynn, P. (1999). Data clustering: A review, ACM Computing Surveys, 31 (3), 264–323.
7. Mazid, M.M., Ali, S., and Tickle, K.S. (2008). Finding an unique Association Rule Mining Algorithm based on data characteristics, In Proceedings of the IEEE/ICECE, Dec 2008, Dhaka, Bangladesh.
8. Scheffer, T. Finding association rules that trade support optimally against confidence. Intelligent Data Analysis, 9(4), 381-395, 2005.
9. ter Braak, C. J. F. (1990). Interpreting canonical correlation analysis through biplots of structure correlations and weights. Psychometrika, 55, 519-531.