Issue Brief

# Risk Modeling of Student Post-School Employment Outcomes: Analysis of Stage I Variables

by Michael West.

For nearly 20 years, the National Longitudinal Transition Study (NLTS) has provided educators, policy-makers, and researchers with a national picture of students with disabilities in secondary education and their transition to adulthood.

The original NLTS was designed and conducted by SRI International based in Menlo Park, CA, from 1985 through 1993 under a contract with the U.S. Department of Education, Office of Special Education Programs (OSEP).

The second round of the NLTS, the NLTS-2, began in 2001 again under the sponsorship of OSEP and the Institute of Education Sciences (IES). The NLTS-2 includes 11,270 youth nationwide who were ages 13 through 16 at the start of the study, and were followed for up to eight years following school exit to investigate such areas as community engagement, postsecondary education, and social interactions.

**What we Know**

One of the critical areas addressed by the NLTS and the NLTS-2 is student engagement in employment following school exit. Most recently, Newman et al. (2011) examined the NLTS-2 data and found that 60% of students with disabilities were working for pay outside the home up to eight years post-school, which was not significantly different from their non-disabled cohorts. Moreover, 91% had been employed for some period of time following school exit, with 31% having been employed for a period of time but unemployed at the time of the interview. However, Newman et al. found that employment rates varied across many factors, including disability group status, student sex and race, parents’ household income, and others.

Carter, Austin, and Trainor (2011) focused on students with intellectual disabilities who were included in the NLTS-2. They found that 26% were working for pay, although nearly half (46%) were working in settings where most of their coworkers also had disabilities, such as work crews, enclaves, and sheltered workshops. Using a logistic regression model, they found that those who were employed in competitive, integrated workplaces (1) had engaged in a paid, community-based job while in secondary school; (2) were more likely to be male; (3) were more independent in self-care; (4) had higher social skills; (5) had more household responsibilities during adolescence; and (6) had higher parental expectations related to future work.

Several of these variables have been found to be predictive of post-school employment success by other, non-NLTS studies (i.e., Shandra & Hogan, 2008; White & Weiner, 2004). Other studies have found such factors as student gender and race to influence transition outcomes (i.e., Flexor et al., 2011).

**Advancing Knowledge and Practice**

Closely associated with prediction modeling is the concept of risk modeling. Risk modeling can be loosely defined as the identification, aggregation, and quantification of risks to individuals, organizations, governments, etc., as the result of adverse events or circumstances. For example, the banking, credit, and insurance industries often use risk modeling to identify the factors or combination of factors that are likely to lead to customer default, bankruptcy, automobile accidents, death, and so on.

Under a grant from the U.S. Department of Education, National Institute on Disability and Rehabilitation Research (NIDRR), the Center on Transition to Employment for Youth with Disabilities has undertaken a novel approach to examine the NLTS-2 data and develop a risk model for poor transition outcomes related to post-school employment.

The study will include a multitude of NLTS-2 data elements related to student and family demographics, student educational program, and school and community characteristics. These data elements will include static variables (i.e., those that cannot be manipulated, such as student race and gender) and elements of the school or student educational program that are alterable through interventions, such as participation of adult services in the transition planning process.

Initial analysis will determine the combination of static factors that lead to poor employment outcomes as measured by whether or not the student worked at any paid position since leaving school. Following that, we will analyze the alterable variables that appear to mitigate the risk factors, that is, improve the likelihood of employment. Future analyses will use a combination of employment related factors to develop better measurement models of employment outcomes in order to evaluate the quality and duration of students’ employment experiences.

Partition modeling via the AnswerTree statistical software will be used for data mining. Nong (2003) defined data mining as an array of techniques that are used to extract hidden predictive information from large databases. Specifically, data mining is concerned with inductive model building by the ex post facto explanation of a basic set of interrelated propositions. The explanation forms a middle range theory that becomes the basis for future hypothesis testing. Data mining has been used extensively in business for evaluating credit, predicting wages, and segmenting the marketplace (Nong, 2003; SPSS, 1998). Increasingly, data mining techniques are being used to solve pattern recognition problems in large health care and rehabilitation databases with encouraging results (Chan, McMahon, Cheing, Rosenthal, & Bezyak, 2005; Chan, Wong, Rosenthal, Kundu, & Dutta, 2005). Specifically, the Exhaustive Chi-squared Automatic Interaction Detector (Exhaustive CHAID) technique has been used successfully with the Rehabilitation Services Administration Form 911 data set to study the interaction among race, gender, and severity of disability and their effect on employment outcomes of people with disabilities in vocational rehabilitation (Chan, Wong et al., 2005). The technique also has been used to predict workplace discrimination based on the social-cognitive theory/attribution theory of stigmatization of disability (Chan McMahon et al., 2005).

In the current study, exhaustive CHAID will be used to build a classification tree. This technique uses a systematic algorithm to detect the strongest association between predictors (e.g., race/ethnicity, gender, types of disability, and socioeconomic status) and the outcome variable (i.e., employed vs. not employed) through a comprehensive search of the predictors (risk factors) and the levels of predictors from the entire set that show the most differentiation on the outcome variable. The degree of differentiation is depicted sequentially in a decision tree format to show the optimally split predictors. Using the exhaustive CHAID analysis we can “detect” risk variables that can be used to differentiate groups with the high rates of employment success from groups with low rates of employment success, while simultaneously prioritizing and entering the predictor variables based on their predictive ability. To control for Type I error, the Bonferroni feature was used to adjust the alpha levels for identifying significant homogeneous subgroups while maintaining the overall alpha at the .01 level. For validation, we will use a tenfold cross-validation by splitting the data into ten subsamples. Ten trees are generated by dropping each time a different subsample. For each tree, the misclassification rate is computed on the dropped out data. The cross-validated error estimate for the overall tree will be computed as the average of the error estimates for all of these trees.

The findings from this study will identify static factors that contribute to risks for poor employment outcomes following school exit for students with disabilities. It also will identify student, programmatic, and school factors that are alterable and which contributed to successful outcomes. These alterable factors can provide evidence leading to the development or expansion of interventions or strategies that can improve employment rates and employment quality of students with disabilities in high risk groups.

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