
Identifying Early Warning Indicators for High School Dropouts

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Background

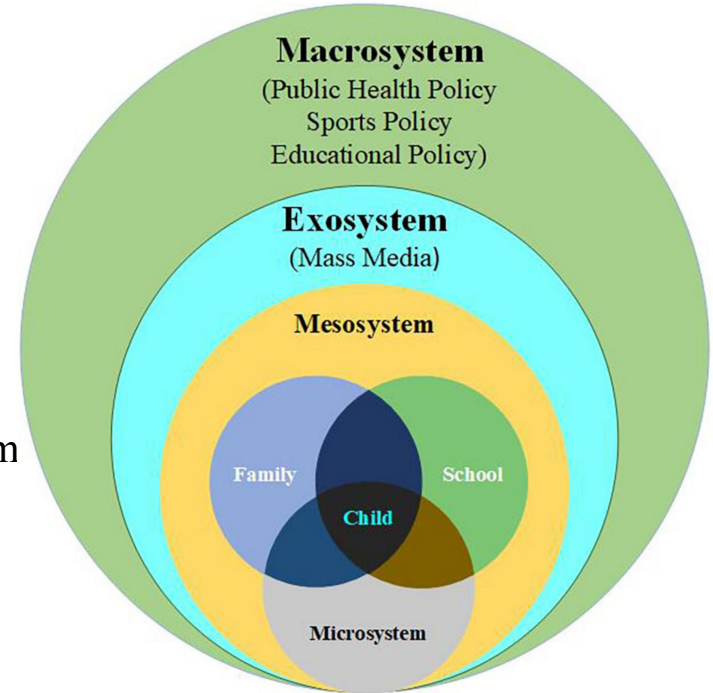
- High school dropouts has been an important issue to be handled at all levels of education.
- $\text{Unemployment rate}_{\text{less than high school}} > 3 * \text{Unemployment rate}_{\text{bachelor degree or more}}$
- This disparity was especially pronounced during the COVID-19 pandemic, when the average unemployment rate for bachelor's degree holders was approximately 8%, but 17% for high school graduates who had not enrolled in any college (Bureau of Labor Statistics, 2022).
- Therefore, researchers are interested in identifying predictors of high school dropouts to aid in its prevention.

Motivation

- There have been some studies used machine learning algorithms to identify potential predictors, such as random forest (Chung & Lee, 2019; Sara et al., 2015), support vector machine, boosted regression, and post-Lasso (Sansone, 2019).
- However, most previous studies:
 - a. Examined immutable predictors (i.e., variables that students, teachers, administrators, family and community members have partial or no control over)
 - b. Selected predictors without theoretical grounding
 - c. Have not tried the deep learning algorithm
- This study aims to use deep learning algorithms to examine mutable/ actionable predictors selected based on Bronfenbrenner's ecological system theory.

Theoretical Framework

- Bronfenbrenner's ecological system theory:
 - a. Microsystem: directly interact with student
 - b. Mesosystem: interaction between microsystem
 - c. Exosystem: indirectly impact student
 - d. Macrosystem: societal and cultural contexts
- Factors from individuals, microsystems, and mesosystem have greatest impact on individual development.



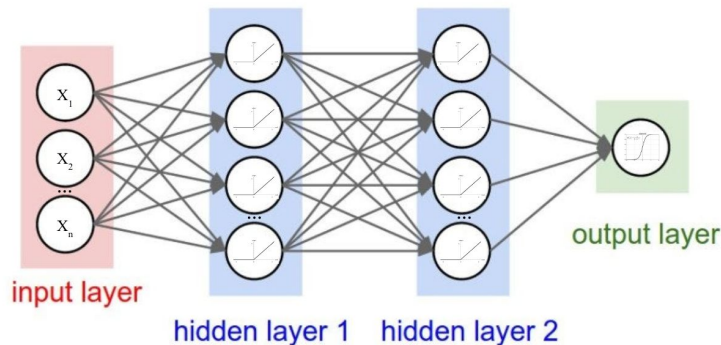
Method

- **Data:** High School Longitudinal Study of 2009 (HSL:09)
(1st round in 2009, 9th grade → 2nd round in 2012, 12th grade → 3rd round in 2016)
- **Sample:** 23,503 9th graders from 944 schools, and their parents, teachers, school principals
- **Data pre-processing:**
 - a. Removing cases that parental questionnaire was not answered by their biological/stepparents
 - b. Removing variables with a missing rate of 30% or higher
 - c. Imputing missing values using Random Forest imputation
 - d. Removing predictors that were not correlate with high school dropouts (1=dropout, 0= not dropout)
 - e. Balancing the samples in two dropout group using Synthetic Minority Oversampling Technique-Nominal
- **Final data:** 38 predictors, 22,612 (11,306 for each class) 9th graders.

Method

- **Deep learning algorithm:**

- Keras package in Python to build a deep neural network model via Tensorflow.
- Four layers:
 1. Input layer
 2. 1st hidden layer: 128 nodes, Rectified Linear Unit (ReLU) activation function
 3. 2nd hidden layer: 32 nodes, ReLU function
 4. Output layers: 1 node, the sigmoid function



Results

- Feature importance:

- a. GPA

- b. Teacher expectations

| Predictors | Weight (Feature Importance) |
|-------------------------------------|-----------------------------|
| The 9th grade GPA | 0.1381 ± 0.0044 |
| Teacher expectations | 0.0550 ± 0.0077 |
| Family socioeconomic status | 0.0480 ± 0.0059 |
| Counselor expectations | 0.0452 ± 0.0058 |
| Mothers' educational level | 0.0428 ± 0.0041 |
| Principal expectations | 0.0415 ± 0.0052 |
| Fathers' educational level | 0.0379 ± 0.0044 |
| Students' sense of school belonging | 0.0355 ± 0.0043 |
| Students' college enrollment status | 0.0355 ± 0.0037 |
| School climate | 0.0331 ± 0.0058 |

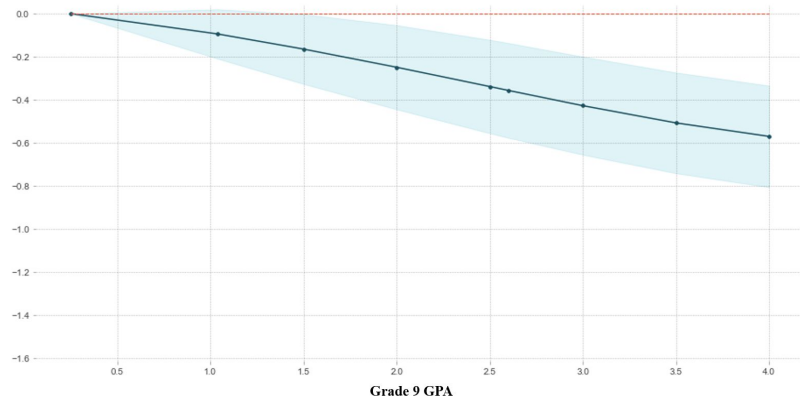
Results

- **GPA:**

The higher GPA, the less dropout

Partial Dependence Plot for Grade 9 GPA

Number of unique grid points: 9

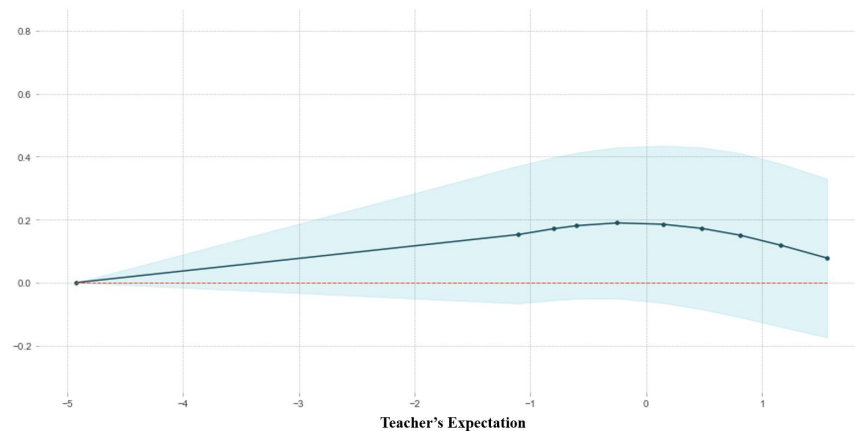


- **Teacher expectation:**

A quadratic relationship between expectation and dropout

Partial Dependence Plot for Teacher's Expectation

Number of unique grid points: 10



Discussion

- Using a deep learning system, the current study identified the top ten predictors of dropouts, seven of which are actional predictors.
- GPA and future-oriented goals (i.e., teacher expectation, counselor expectation, principal expectations) are two most important predictors.
 - High GPA could protect students from dropping out of high school, and moderate level expectations from others are the most beneficial.
- There are many studies examined the role of educational expectations to students, which is a good news to educational practitioners.
 - We can encourage students to commit themselves to meaningful long-term educational goals, seek to benefit from their educational experiences, which would lead them to monitor their progress toward their goals.

Discussion

- The quadratic relationship between the expectation and high school dropouts indicates that the role of expectation is a mixed blessing. This quadratic pattern was also found in the relationship between expectation and students' academic achievement (He et al., 2022).
- The potential moderators could be control and autonomy support, which were framed in both self-determination theory (Joussemet et al., 2008; Moe et al., 2020; Schiffrin et al., 2019) and the Beliefs, Expectations, Autonomy Support, and Relationships (BEAR) model (Froiland, 2021).

Discussion

- **Limitations**

- a. It will be better, if we compared the performance of deep learning with other ML algorithms
- b. We manually selected original 67 predictors from 1000+ predictors in the data pool based on they ecological system theory, which may introduce potential biases in the results.

- **Contributions**

- a. This is the first attempt to use deep learning algorithms to identify potential predictors.
- b. This study added evidence to the importance of educational expectations, as well as its' relationship with high school dropouts.

Thank you for your listening !

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