BIAS IN BIG DATA WITHIN HIGHER EDUCATION

AUDREY J. MURRELL, PH.D., ACTING DEAN
UNIVERSITY OF PITTSBURGH~HONORS COLLEGE
AMURRELL@PITT.EDU | @PROFAJMURRELL

PittHonors
Cross boundaries.
FORGE AHEAD.

THE PROMISE OF "BIG DATA" IN HIGHER EDUCATION

- To gain a competitive advantage on recruiting and maintaining students, institutions have begun analyzing demographic and performance data to predict whether a student will enroll at an institution and if they will stay on track with their courses or require additional support to ensure they don't fall behind.
- Analyzing past student data to predict what current and prospective students might do has helped institutions meet their annual enrollment and revenue goals with more targeted recruiting and more strategic use of institutional aid.
- Predictive analytics has also allowed colleges to better tailor their advising services and personalize learning to improve student outcomes as well as institutional efficiencies.

BIG DATA: PROMISE VERSUS PITFALL?

While it is true that there is power in predictive analytics, "big data" is not a panacea especially within the context of diversity and inclusion. Concepts such as "AI" and "machine learning" are assumed to be neutral by definition, yet all predictive models are shaped by human judgment, which we know falls far short of being error-free:

- Implicit Bias
- Association Bias
- Confirmation Bias
- Illusory Correlation

IMPLICIT BIAS

Implicit bias (or implicit social cognition) refers to the attitudes or stereotypes that affect our understanding, actions, and decisions in an *unconscious manner*.

- Encompass both favorable and unfavorable assessments
- Are activated involuntarily and without an individual's awareness or intention
- Reside deep in the subconscious and not accessible through introspection
- Contribute to feelings and attitudes about other people based on salient characteristics such as race, ethnicity, age, nationality, appearance, etc.

Implicit biases are:

- Pervasive
- Not mutually exclusive and may even reinforce each other
- Not necessarily align with our declared beliefs
- Likely to favor our own ingroup
- Malleable and can be changed over time and with targeted intervention

ASSOCIATION BIAS

- We automatically connect a stimulus (thing/person) with positive or negative feelings. We seek out positive associations and attempt to remove negative ones. The more vivid the event or salient a group/person, the easier it is to remember.
- Predictive analytics models/algorithms are impact by an association bias that occurs when the data used within any predictive algorithm or model has inherent biases associated with gender, race, ethnicity, culture, etc.
- Example: Using zip-codes to predict outcomes, preferences or other key factors ignores the historical impact of redlining, which has a demonstrated negative impact on historically disadvantages families.

CONFIRMATION BIAS

- When people tend to look for and use the information to support their own preexisting ideas or beliefs.
- Information that fails to support their thinking is disregarded or discarded. This can impact both the kind of data that is selected (or not selected), as well as the interpretation of which data is relevant or appropriate for our so-called unbiased models.
- Confirmation bias often happens when we want certain ideas to be true. This leads individuals to stop gathering information when the retrieved evidence confirms their own viewpoints, which can lead to preconceived opinions (prejudices) that are not based on reason or factual knowledge.
- <u>Example</u>: Eliminating or disregarding "outliers" within data that do not follow what is assumed to be the normative or expected outcomes and/or data patterns

ILLUSORY CORRELATION

- The phenomenon of perceiving a relationship between variables (typically people, events, or behaviors) even when no such relationship exists. A false association may be formed because rare or novel occurrences are more salient and therefore tend to capture one's attention.
- Concluding or inferring that an association (correlation) is a causal relationship. These biases can include both distinctiveness-based and expectancy-based illusory correlation.
- Example: Drawing conclusions that education outcomes or behaviors that are observed to happen more frequently with a particular racial/gender/ethnic group is casual, ignoring underlying or unmeasured factors.

COMBATING BIAS IN HIGHER EDUCATION BIG DATA

- Own up to the fact that the selection of data, the definition of models, the interpretations of findings and the actions taken based on these models are inescapably influenced by the same implicit biases of everyday human behavior.
- Placing the label of predictive analytics on data does not ensure that errors in judgment will not take place - nor does it mitigate the fact that these biases are extremely problematic for achieving goals of diversity and inclusion in higher education.
- We must constantly challenge the source, assumptions, method of data gathering, the interpretation and the use of data.
- We should focus our attention and our resources on not merely modeling the trajectories of outcomes but also on the innovative approaches to changing or disrupting them.

SOME FINAL THOUGHTS…..

- We must avoid the "easy solutions" that are often provided by "big data" solutions and do the hard work of understanding the role the historical boundaries, campus culture/climate, student-teacher interactions and institutional racism/sexism play in producing and maintaining disparities in student outcomes.
- Some people may continue to argue that "big data" is neutral and unprejudiced. They are wrong. We must continue to move forward with an embrace of data-driven decisions and predictive models. And while doing so, we must be forever mindful that while data may not discriminate, people still do.

QUESTIONS AND DISCUSSION