People Analytics & Employment Selection: Opportunities & Concerns

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Outline

- Introduction & Overview: People Analytics
  - Promise & Danger
- Foundational Laws & Regulations
  - UG ESP
    - Measuring Adverse Impact
    - Measuring Validity
- Brainstorming research interests/ideas
People Analytics

- AKA Workforce Analytics, Talent Analytics, HR Analytics...
- The application of diverse data sources and machine learning techniques to employment decisions
  - Employment Selection
    - e.g. Sourcing, Hiring, Promotion, Discharge
  - Pay
  - Succession Planning
  - Workplace Design
- Data can be passively compiled or collected directly
What do People Analytics tools look like?

<table>
<thead>
<tr>
<th>Passive Recruiting tools and screens of passive candidates</th>
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<tbody>
<tr>
<td>Facial expression/tone of voice/language pattern analysis from recorded interviews</td>
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<tr>
<td>Profiling tools that allow employers to select candidates who are similar to a particular profile</td>
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<td>Simple or complex ‘games’ that collect job fitness measurements</td>
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<td>Tools designed to track employee movement and communication patterns</td>
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<tr>
<td>?????? There seems to be a new tool on the market every week</td>
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The Promise

- **Efficiency**
  - Automated & scalable
  - Predict rather than describe
  - Improve the candidate & employee experience

- **Effectiveness**
  - Demonstrate ROI

- **Job Relatedness**
  - Criterion validity is built into the process (cross validation)

- **Fairness**
  - Minimize the likelihood of intentional discrimination
  - Remove bias while retaining signal
  - Automate Adverse Impact Analysis
  - Automate the search for less discriminatory alternatives
The Danger

- **Job Relatedness**
  - Construct and Content validity evidence often missing
  - Traditional job analysis often missing

- **Fairness**
  - Algorithms replicate previous decisions
  - If training data is homogeneous, algorithm results will tend to perpetuate that homogeneity in race, gender, age, etc.

- **Data and computer scientists tend not to be trained in issues of fairness or job-relatedness**
  - Employment decisions are much more high-stakes and better-regulated than marketing decisions
  - Optimizing on **accuracy** and not **fairness**.
  - **Predictive** versus **explanatory** analytics
Foundational Laws and Regulations Enforced by EEOC

- Title VII of the Civil Rights Act - protections on the basis of race, sex, religion & national origin.
  - Uniform Guidelines on Employee Selection Procedures (UGESP)
- Title I of the Americans with Disabilities Act - makes it illegal to discriminate against a person with a disability
- Age Discrimination in Employment Act - protects people who are age 40 or older from discrimination because of age.
- Genetic Information Non-Discrimination Act - protections for genetic information.
  - Including information about family members, as well as information about any disease, disorder or condition of an individual's family members (family medical history).
Theories of Discrimination

- Employment tests and screens can be very effective, but their use must be lawful
  - Disparate Treatment: Cannot be used to intentionally screen out people of a certain race, sex, national origin, religion, disability, or age (40 or older).
  - Disparate Impact: Even if the discrimination is not intentional, these measures cannot screen on protected characteristics unless the Employer can properly justify their use
The Uniform Guidelines (EEOC et al., 1978)

If there is statistical evidence of adverse (disparate) impact the employer must be able to demonstrate:

- The validity of the procedure
  - Job-relatedness
- (Test prep) Fairness
  - Applicants/employees had equal access to any available preparation materials
- Attempts to identify equally-valid alternative selection devices with less impact
- Additional attempts to reduce adverse impact

§ 1607.4 (D) Adverse impact and the ‘four-fifths rule.’ A selection rate for any race, sex, or ethnic group which is less than four-fifths (4/5) (or eighty percent) of the rate for the group with the highest rate will generally be regarded by the Federal enforcement agencies as evidence of adverse impact.

- Smaller differences in selection rate may nevertheless constitute adverse impact, where they are significant in both statistical (p < .05) and practical terms or where a user’s actions have discouraged applicants.
Measuring Validity

- **Criterion-Related Validity** - The extent to which test scores are systematically related to a relevant criterion
  - Criterion usually defined as some measure of job performance
  - Measures of job performance themselves may be biased (e.g. absenteeism)
  - Reverse-engineering to demonstrate criterion-related validity, providing built-in defense

- **Content Validity** - The extent to which the items on a test are representative of the construct the test measures
  - In employment, the construct the test measures is the ability to do the job
  - Requires a qualitative/quantitative study of the job itself, identification of its essential functions, KSAs

- **Construct Validity** - Involves accumulating evidence that a test is based on sound psychological theory
  - Convergent & divergent evidence that the construct is what you think it is
§ Sec. 1607.15 Documentation of Impact and Validity Evidence

- Users [with more than 100 employees] of selection procedures should maintain and have available for each job, records or other information showing whether the total selection process for that job has an adverse impact. Adverse impact determinations should be made at least annually for each such group which constitutes at least 2 percent of the labor force.

- Where a total selection process for a job has an adverse impact, the user should maintain and have available records or other information showing which components have an adverse impact.

- Where there is evidence of adverse impact, the employer should have evidence of:
  - Validity of the selection device
  - Attempts to reduce AI
People Analytics has to do with the application of diverse data sources and machine learning techniques to employment decisions.

Foundational laws to protect people from unfair decisions based on protected characteristics.

UGESP is a set of guidelines for using employment selection tools without violating Title VII of the Civil Right Act.

- It establishes the concept of disparate (adverse) impact, which need not be intentional.
- Gives a general outline: Device should be fair, and job-related. Should optimize on fairness.

UGESP is now 40 years old. It was not written with machine learning or people analytics approaches in mind.

- Some say it's not equipped to handle more contemporary techniques.
- It's likely that, at some point, regulatory agencies will pass guidance to address.
- It's likely that accumulating case law will address.
Brainstorming Research Interests

- **Fairness**
  - Investigating relationships between passive data and protected characteristics
    - Or intermediary variables related to both?
    - Including age, genetic information, disabilities

- **Validity**
  - Investigating reliability of passively-collected data
    - Can it lead to false assumptions about people?
  - Construct: Is personal history really related to career, work, job performance?
    - Biodata in I/O psychology
    - Example: credit history and job performance...?

- **Explanatory** versus **predictive** analytics; non-biased comparisons
  - Help regulators understand this
  - What’s the model for properly combining the two?
Questions :: Comments :: Ideas

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