YOU'RE FIRED! A CASE FOR AGENCY MODERATION OF MACHINE DATA IN THE EMPLOYMENT CONTEXT

Timothy M. Snyder[*]

INTRODUCTION

Imagine a world where computer programs govern your entire work experience: from application, to promotion, to exit. These programs do not simply inform corporate Talent Management about you; they leverage complex algorithms to predict your future performance and make employment decisions that deeply affect you.[1]

Upon applying to a job, Talent Management's program employs deep web crawlers to collect millions of data points about you—prior job performance and educational history, social preferences, favorite browser, your interest in foreign travel—and determines you are an excellent fit for the job.[2] Once hired, this same program monitors your digital work activity—the amount of time you spend on certain activities, where you eat lunch, your browser activities, key words in your emails[3]—and time after time, you are

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* George Mason University School of Law, J.D. Candidate, May 2018; Symposium Editor, GEORGE MASON LAW REVIEW 2016-2017; Patrick Henry College, B.A. Government, 2010. Special thanks to Kathleen Garman, Camilla Hundley, Kyle Simpson, and my wife, Irina Snyder, for their help in publishing this article.

1 *See Descriptive, Predictive, and Prescriptive Analytics Explained*, HALO BI, https://halobi.com/2014/10/descriptive-predictive-and-prescriptive-analytics-explained/ (last visited Aug. 21, 2016) [hereinafter "HALO BI"]. The author describes predictive analytics as the use of "statistical models and forecast[] techniques to understand the future and answer: 'What could happen?'" Prescriptive analytics "use[s] optimization and simulation algorithms to [advise] on possible outcomes and answer: 'What should we do?'"

2 *See, e.g.*, Mark Burdon & Paul Harpur, *Re-Conceptualising Privacy and Discrimination in an Age of Talent Analytics*, 37 U.N.S.W. L.J. 679, 680 (2014) (noting that "the web browser [which] an applicant used to upload their job application or when and where an employee has their lunch are now potentially relevant factors in recruitment and retention decisions") (footnotes omitted); *Upgrade and Unlock Everything on Joe Smith*, SPOKEO, https://www.spokeo.com/purchase?pid=1181751631&q=Joe+Smith&url=%2FJoe-Smith%2FNew-Jersey%2FOaklyn%2Fp1181751631 (last visited Aug. 21, 2016); *see also* Complaint 4–6, United States v. Spokeo, Inc., No. 2:12-cv-05001-MMM-SH (C.D. Cal. Jun. 7, 2012), (alleging that Spokeo developed a software product that aggregated profiles on individuals and sold the aggregated candidate profiles to prospective employers without proper consumer protections); *What Can You Do With Spokeo?*, SPOKEO, http://www.spokeo.com/about (last visited Aug. 21, 2016) (describing its product as allowing a person to search "billions of records in an instant").

3 *See* Robert Sprague, *Welcome to the Machine: Privacy and Workplace Implications of Predictive Analytics*, 21 RICH. J.L. & TECH. 1, 34 (2014) (describing companies using advanced workforce analytics as able to capture "every email, instant message, phone call, line of written code, and mouse-click . . . .

passed up for promotion.[4] You speak to Talent Management, but all you are told is there was another candidate who was a better fit for the position. What they do not tell you, but what you suspect, is that Talent Management's program did not think you were right for the promotion, that there were factors in your dataset that predicted you would not be successful.[5] You ask Talent Management for a program report, so you can ensure the accuracy and completeness of the data. But they tell you that they are not required to provide you a report. Since the company is not a Consumer Reporting Agency ("CRA")[6] and Talent Management is only using data it collected itself during your term of employment, it is not required to divulge any reason for an adverse action on your application for promotion.[7]

Then, one day, you are let go from your job. The company is "moving in a different direction," and you are no longer "the right fit." What you suspect, but will never know for certain, is that Talent Management's program identified a pattern in your work data and predicted you would not be successful based on the company's projected direction, and the program recommended you be let go.

You begin your job search almost immediately. As you talk to your friends, you discover that many of them are in the same situation and have similar stories. At first, you think it is just a coincidence, but then you begin to wonder if it is because you are all part of the same minority. You consult a lawyer to discuss options. She tells you that a discrimination case is an

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Where a worker eats lunch during the workday may also be monitored and analyzed.") (footnotes omitted).

4 *See* Thomas H. Davenport et al., *Competing on Talent Analytics*, HARV. BUS. REV., Oct. 2010, at 2, 4 (describing Lockheed Martin's software program that aggregates individual employee performance against organizational objects and interacts with its knowledge management data to select high potential employees for "special programs" or to "monitor employees who need improvement").

5 *See, e.g.*, *id.* at 3–4.

6 As defined by the Fair Credit Reporting Act ("FCRA"), 15 U.S.C. § 1681a(f) (2012).

7 *See* FED. TRADE COMM'N, 40 YEARS OF EXPERIENCE WITH THE FAIR CREDIT REPORTING ACT 23–24 (2011), https://www.ftc.gov/sites/default/files/documents/reports/40-years-experience-fair-credit-reporting-act-ftc-staff-report-summary-interpretations/110720fcrareport.pdf [hereinafter "FTC, 40 YEARS OF EXPERIENCE"] ("Section 603(d)(2)(A)(i) excludes from the definition of consumer report 'any report containing information solely as to transactions or experiences between the consumer and the person making the report.' . . . A communication from a former or current employer to a CRA or other third party, involving only transactions between the consumer (the employee or applicant) and the person making the report (the current or former employer) is not a consumer report because it is based on the 'experiences between the consumer and the person making the report.'" (footnote omitted)).

uphill battle at best.[8] Rather than risk incurring the substantial costs of litigation,[9] you discard the idea and continue your job search, hoping that the Talent Management program at another corporation will predict your success and recommend you for employment.

Because the technology currently exists to create the dystopian world described above, and corporate talent management teams are rapidly adopting that technology, this Comment analyzes the two primary regulatory sources relevant to predictive talent analytics: the Federal Trade Commission ("FTC") vis-à-vis the Fair Credit Reporting Act ("FCRA")[10] and Federal Trade Commission Act ("FTCA")[11] and the Equal Employment Opportunity Commission ("EEOC") vis-à-vis Title VII.[12] Literature to date has focused largely on the dangers of big data with respect to privacy and the inadequacy of existing oversight to properly protect consumers.[13] Rather than focus on privacy or big data generally, this Comment provides a narrow look at big data within the context of talent analytics software and describes the comparative limits of existing regulatory authority within this domain. The FTC and EEOC serve as the primary regulatory sources in analytics.[14] To that end, this Comment compares the scope of EEOC and FTC statutory authority and concludes that, due to the technical nature of predictive talent analytics and the statutory structure of the business necessity exception,[15] the EEOC should apply its authority under Title VII[16] conservatively, primarily applying it only

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8 *See* Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671, 729 (2016) (describing Title VII's inefficacy at resolving big data cases).

9 Jonathan D. Glater, *The Cost of Not Settling a Lawsuit*, N.Y. TIMES, Aug. 7, 2008, at C1 (reporting that "on average, getting it wrong cost plaintiffs . . . about $43,000").

10 The Consumer Financial Protection Bureau (CFPB) enforces certain, relevant, aspects of the FCRA since enactment of the Dodd-Frank Act in 2011. Thoroughly distinguishing the authority of the FTC and CFPB is out-of-scope for this Comment. Suffice to say that both the FTC and CFPB retain authority under the FCRA and could work jointly to regulate predictive talent analytics. *See* Andrew M. Smith & Peter Gilbert, *Fair Credit Reporting Act Update—2011*, 67 BUS. LAW. 585, 586 (2011) (explaining that "the CFPA amended the FCRA to provide the CFPB with general enforcement powers . . . but the FTC continues to maintain its general enforcement jurisdiction under the FCRA as well").

11 15 U.S.C. § 57a (2012) (FTCA).

12 15 USC § 1681s(a)(1) (2012) (FCRA); 42 U.S.C § 2000e-4 (2012) (Title VII).

13 *See*, *e.g.*, Omer Tene & Jules Polonetsky, *Big Data for All: Privacy and User Control in the Age of Analytics*, 11 NW. J. TECH. & INTELL. PROP. 239, 251–56 (2013) (describing the privacy dangers of big data as well as its exclusionary potential).

14 *See* FED. TRADE COMM'N, BIG DATA: A TOOL OF INCLUSION OR EXCLUSION? 13, 18 (2016), https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf.

15 *See* Title VII, 42 U.S.C § 2000e-2(k)(1)(A)(i) (2012) ("An unlawful employment practice . . . is established . . . only if a complaining party demonstrates that a respondent uses a particular employment practice that causes a disparate impact . . . and the respondent fails to demonstrate that the challenged practice is job related for the position in question and consistent with business necessity . . . .").

16 42 U.S.C. § 2000e-4(g) (2012).

to explicit algorithmic discrimination under its disparate treatment provision.[17] The FTC, on the other hand, should use its statutory authority under the FCRA[18] and FTCA[19] expansively within the employment context. These changes will ensure employees receive similar protections from the adverse effects of predictive talent analytics that the public currently enjoys with respect to their credit scores.

Part I of this Comment contextualizes talent analytics technology and its primary regulatory sources to enable Part II's comparison of the EEOC and FTC as future regulators of the growing talent analytics industry. Part II compares the efficacy of EEOC enforcement of Title VII to FTC enforcement of the FCRA and FTCA by predicting the likely trajectory of statutory application to the talent analytics industry based on an analysis of current precedent and agency enforcement action. This Comment concludes that the FTC should take a lead role in regulating talent analytics software and responds to possible objections.

I. BACKGROUND

Talent analytics software is uniquely difficult to regulate due to its complexity.[20] Nevertheless, both the EEOC and FTC are making early efforts regulate this emerging industry.[21] The first section identifies the problems posed by talent analytics and describes the unique characteristics that make talent analytics software both difficult to regulate and of immense value to businesses. The second and third parts look at statutory protections and how the EEOC and FTC have implemented them, respectively.

A. *The Problem: The Inevitability and Unique Risks Posed By Predictive Talent Analytics*

This section describes the economic drivers and varieties of predictive talent analytics as well as the risks posed in terms of fairness to individual employees and discriminatory affects towards classes of people. Predictive talent analytics software programs have already assumed a large and growing market share, but talent management teams are particularly ill-trained in proper data analytics practices. Understanding the risks inherent in predictive

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17 42 U.S.C § 2000e-2(a)(1) (2012) ("It shall be an unlawful employment practice . . . to fail or refuse to hire or to discharge any individual, or otherwise to discriminate against any individual with respect to his compensation, terms, conditions, or privileges of employment, because of such individual's race, color, religion, sex, or national origin . . . .").

18 15 U.S.C. § 1681s(a)(1) (2012).

19 15 U.S.C. § 45(a)(2) (2012).

20 *See infra* Part I.A.2

21 *See infra* Part I.B. & C.

analytics, particularly within the talent management context, sets the stage for justifying an increased role for the FTC to provide additional oversight of predictive talent analytics software products.[22]

1. Predictive Talent Analytics Future Within Talent Management

Predictive talent analytics is here to stay because it makes business sense.[23] Talent problems are large cost drivers at most companies,[24] and traditional talent management groups are ripe for change.[25] Not only do companies find it difficult to recruit and retain the right employees, but employee disengagement across the board is high, and employee belief in their organizations remains stubbornly low, which comes at a high cost.[26] In a two-year study of the American workplace, Gallup estimated that "active disengagement" costs American companies $450 billion to $550 billion every year.[27] Not surprisingly, leading consulting firms consider talent management to be on the cusp of digital disruption.[28] One study indicated that "[eighty-five] percent of global organizations felt the need to 'transform HR to meet new business priorities right now' . . . or 'within the next one to three years.'"[29]

22 This section sets the stage both in a policy and a legal sense. Normatively, the risks associated with talent analytics justify increased oversight. As a strictly legal matter, the FTC's Section 5 authority under the FTCA requires a balancing test be conducted for its third prong. *See* discussion *infra* Part II.B.3.

23 Press Release, Deloitte US, Global Human Capital Trends Report 2015: Global Organizations Face Looming Crisis in Engagement and Retention of Employees (March 4, 2015) [hereinafter Deloitte Press Release] (Indicating that the "cognitive power of computers and software is challenging organizations to rethink the design of work and the capabilities their employees need" and reporting that "[f]ifty eight percent of leaders indicate that 'redesigning work with computing as talent' is an important trend").

24 *See, e.g.*, *id.* (recognizing "that a general lack of skills is likely to impede business growth, [eighty-five] percent of HR and business leaders ranked learning and development as a top issue"); *see also* KPMG INT'L, TIME FOR A MORE HOLISTIC APPROACH TO TALENT RISK 5 (2013), https://www.kpmg.com/Global/en/IssuesAndInsights/ArticlesPublications/Documents/global-talent-related-risk.pdf (reporting on the top ten talent risks based on a survey of talent leaders).

25 Bersin by Deloitte, *Build Capability in HR Business Partners and "Business HR,"* DELOITTE 1 (2015), http://www.bersin.com/uploadedFiles/hrbp-blueprint-Brief.pdf?aliId=71727708 [hereinafter "Bersin by Deloitte"](reporting results from 300 surveyed companies that "[eight-five] percent of global organizations felt the need to [either] 'transform HR to meet new business priorities right now' ([fifty-seven] percent) or 'within the next one to three years' ([twenty-eight] percent). Yet our data also indicates that, for the most part, HR operational structures and norms have not changed since 1995.") (footnotes omitted).

26 *See* Deloitte Press Release, *supra* note 23.

27 GALLUP, STATE OF THE AMERICAN WORKPLACE: EMPLOYEE ENGAGEMENT INSIGHTS FOR U.S. BUSINESS LEADERS 9 (2013).

28 Accenture calls it a "radical" digital disruption, and believes the future of talent management teams are smaller and more digitally-savvy. TIM GOOD ET AL., TRENDS RESHAPING THE FUTURE OF HR: DIGITAL RADICALLY DISRUPTS HR 11 (2015).

29 Bersin by Deloitte, *supra* note 25, at 1.

Furthermore, due to talent management's embrace of cloud computing,[30] larger amounts of data will become available and functional for employees and managers across an organization.[31]

Increasingly, companies aim to transform their talent management efforts with big data analytics,[32] and emerging talent analytics products cater to talent management teams by requiring decreasing amounts of human intervention.[33] Indeed, sophisticated talent analytics may be a key competitive differentiator for companies in the near-future.[34] Moreover, talent management's access to large amounts of cross-organizational data makes it a logical center for deploying a predictive data model.[35] However, people on talent management teams generally lack sufficient data analysis skills to properly synthesize human resources data and provide actionable recommendations.[36]

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30 Cloud computing is "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction." PETER MELL & TIMOTHY GRANCE, NATIONAL INSTITUTE OF STANDARDS AND TECHNOLOGY, PUB. NO. 800-145, THE NIST DEFINITION OF CLOUD COMPUTING 2 (2011), http://csrc.nist.gov/publications/nistpubs/800-145/SP800-145.pdf.

31 GOOD ET AL., *supra* note 28, at 11; *see* DELOITTE CONSULTING, LLP & BERSIN BY DELOITTE, GLOBAL HUMAN CAPITAL TRENDS 2014: ENGAGING THE 21ST-CENTURY WORKFORCE 127 (2014), http://dupress.com/wp-content/uploads/2014/04/GlobalHumanCapitalTrends_2014.pdf.

32 Kathryn F. Shen, *The Analytics of Critical Talent Management*, 34 HR PEOPLE AND STRAT. 50, 51–56 (2011) (describing the increased adoption of talent analytics and providing a framework for creating one within a talent management team); *see* Jeanne G. Harris et al., *Talent and Analytics: New Approaches, Higher ROI*, 32 J. OF BUS. STRATEGY 4, 6–8 (2011) (identifying human capital analytics as the solution to re-orient human resources departments towards better business outcomes); *see also Overview of CEB TalentNeuron*, CEB, https://www.cebglobal.com/human-resources.html (last visited Aug. 21, 2016) (illustrating a talent analytics product that aggregates external labor market data to help companies improve their employment practices).

33 *See* Josh Bersin, *The Talent Management Software Market Surges Ahead*, FORBES (Jun. 26, 2014), http://www.forbes.com/sites/joshbersin/2014/06/26/the-talent-management-software-market-surges-ahead/ (providing an overview of talent management vendors and describing the shift to consolidated talent management products); *see also Human Resources (HR) Software Market Forecast 2015-2020*, MARKET RESEARCH MEDIA (May 2, 2014), http://www.marketanalysis.com/?p=338 [hereinafter "Market Research Media"] (citing "talent management sectors (recruiting, training, performance management/BI, and leadership/succession management) as well as [a] shift to [a] software-as-a-service (SaaS) model" to explain the growth in the HR software market).

34 *See, e.g.*, Davenport, *supra* note 4, at 2 (providing a list of leading companies—such as Google, Best Buy, and Sysco—who are "increasingly adopting sophisticated methods of analyzing employee data to enhance their competitive advantage").

35 *See* Emma Snider, *Ready or Not, Here Comes HR Analytics*, TECHTARGET (last accessed Oct. 15, 2016), http://searchfinancialapplications.techtarget.com/feature/Ready-or-not-here-HR-analytics-come (identifying that "HR professionals have long been data collectors, amassing and keeping track of employees' personal information" and that sets the stage for talent analytics). *See also* Davenport, *supra* note 4, at 3 (observing that HR knowledge management databases create "voluminous 'data trails'" that can now be analyzed).

36 Martin Berman-Gorvine, *HR Not Taking Full Advantage of All Workforce Analytics Offers, Survey Reveals*, BLOOMBERG BNA (March 23, 2015), http://www.bna.com/hr-not-taking-n17179

Software products are filling the gap by enabling self-service analytics and integrated dashboards.[37] The talent management software market is large and growing, with some estimating the market size at $10 billion with year-over-year growth,[38] and talent management groups are focused on adapting software solutions to meet the requirements of a twenty-first century workforce.[39] Using these products, talent management teams can integrate their companies' data with the software product to generate dynamic and visually engaging outputs without requiring in-house data science expertise.[40]

2. How Predictive Talent Analytics Work

The output of big data talent analytics comes in three forms: descriptive, prescriptive, and predictive.[41] Descriptive analytics culls through large amounts of data and accurately portrays what is happening within an organization. Several business intelligence products, such as Tableau and Domo, allow users to connect their data to dynamic visualizations to easily communicate their business data.[42] Generally, analytics products that emphasize descriptive outputs rely on humans to connect and manipulate the data;[43] as

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924332/ (reporting that forty-four percent of survey respondents do not leverage workforce intelligence in their planning process citing complexity and lack of resources as reasons); *see also Next Generation Computing and Big Data Analytics: Joint Hearing Before the Subcomm. on Research & Subcomm. on Tech. of the H. Comm. on Sci., Space, and Tech.*, 113th Cong. 8 (2013) (statement of Rep. Larry Bucshon, Chairman, H Comm. on Sci., Space, and Tech.) [hereinafter *Next Generation Computing Joint Hearing*] (identifying a shortfall of 140,000 to 190,000 professionals with sufficient technical data analytics depth across U.S. companies).

37 Josh Bersin, *The People Analytics Market Heats Up with New Cloud Offerings*, FORBES (Nov. 4, 2014), http://www.forbes.com/sites/joshbersin/2014/11/04/the-talent-analytics-market-heats-up-with-new-cloud-offerings/ ("Almost all the new cloud-based HR systems vendors now offer what I'd call 'embedded analytics' solutions built into their software, ready to turn on and analyze employee data right out of the box").

38 Josh Bersin, *Spending On Human Resources Is Up And Why It Really Matters This Year*, JOSHBERSIN.COM (Jan. 16, 2015), http://joshbersin.com/2015/01/spending-on-human-resources-is-up-and-why-it-really-matters-this-year/; *see also* MARKET RESEARCH MEDIA, *supra* note 33.

39 DELOITTE CONSULTING, LLP & BERSIN BY DELOITTE, *supra* note 31, at 127.

40 *Id.* at 128; *see, e.g.*, Press Release, Jaspersoft, NetDimensions and Jaspersoft Unveil Talent Analytics Solution in the Cloud (Jan. 28, 2013), http://www.prnewswire.com/news-releases/netdimensions-and-jaspersoft-unveil-talent-analytics-solution-in-the-cloud-188656471.html.

41 *See* HALO BI, *supra* note 1.

42 *See Product Overview*, DOMO, https://www.domo.com/product#overview (last visited Aug. 21, 2016); *Products: Tableau Desktop*, TABLEAU, http://www.tableau.com/products/desktop (last visited Aug. 21, 2016).

43 *See, e.g.*, Bora Beran, *The Power of R and Visual Analytics*, TABLEAU, http://www.tableau.com/learn/whitepapers/power-r-and-visual-analytics (last visited Aug. 21, 2016) (describing how to integrate R with Tableau to connect your own data model to Tableau's data visualizations).

a result, there is increasing demand for so-called "citizen data scientists"—essentially, ordinary employees who are data savvy.[44]

Predictive and prescriptive analytics,[45] on the other hand, rely on data models to predict the future based on current and past data and prescribe behaviors to achieve the best outcomes.[46] These products use data models that are built upon well-defined methodologies that include evaluating available data, cleansing/preparing the data, building the model, and evaluating the effectiveness of the model.[47]

There are many ways to build a data model, depending on business objectives and available data.[48] Each system begins with a statistical model, with unique tradeoffs and pitfalls.[49] No model is perfect, and each has a number of assumptions that can, over time, validate or invalidate the model, possibly prompting complete abandonment or revision of the model.[50]

Models involving prediction have a wide variety of mathematical tools to measure the relatedness of variables. Each of the formulas that measure relatedness have different tradeoffs and work best in certain contexts for certain measurements.[51] Means of classification and prediction include neural networks,[52] decision trees and rule induction,[53] and Naive Baynes probabilities.[54] For example, one talent management team for a global aerospace manufacturing firm used the Internal Labor Market mapping method[55] to look at

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44 ALEXANDER LINDEN ET AL., PREDICTS 2015: A STEP CHANGE IN THE INDUSTRIALIZATION OF ADVANCED ANALYTICS 7 (2014) (predicting that advances in analytic tools "will enable 'power' users to become their own self-service citizen data scientists").

45 This Comment treats predictive and prescriptive analytics interchangeably as "predictive talent analytics," inasmuch as both forms of big data analytics raise similar concerns in the employment context (just as an unfair or discriminatory prediction raises similar questions as an unfair or discriminatory recommendation).

46 HALO BI, *supra* note 1; *See* Beran, *supra* note 43, at 4 (describing how the combination of the coding language R and Tableau can create prescriptive analytics).

47 Bill Hostmann, *Seek Information Patterns With Data Mining and Predictive Analytics*, GARTNER 1–9 (July 15, 2010) (providing an overview of various "well-defined methodologies").

48 JAMES WU & STEPHEN COGGESHALL, FOUNDATIONS FOR PREDICTIVE ANALYTICS 1–2 (2012) (providing an excellent and comprehensive overview of the models and formulas that form the algorithmic foundation of predictive technologies).

49 *Id.* at 4–5.

50 *See id.* at 4–7.

51 *Id.* at 299–306.

52 This includes nonlinear regression and supervised learning to forecast, score, and classify. These models are difficult to understand and require significant data preprocessing. Hostmann, *supra* note 47, at 1–3.

53 This includes "pairwise or multiwise splits," "if … then rules," and "supervised learning" to conduct risk and churn analysis as well as failure prediction. *Id.* at 6.

54 This includes "posterior probability" and "supervised learning" to conduct classifications and scoring with a high degree of accuracy. *Id.*

55 This method was developed by Mercer. *Welcome to Mercer's Internal Labor Market (ILM) Mapping Tool*, MERCER, https://www.imercer.com/default.aspx?page=ilmTool (last visited Aug. 5, 2016).

"the entire set of employee transactions over time," identify talent risks, and develop a long-term plan to address the findings.[56]

There are hundreds of available formula types to build into a data model, including traditional quantitative statistical calculations as well as sentiment analysis of qualitative data.[57] The advent of widely-available computing enables a process called machine learning to rapidly distill voluminous data, with the data models providing a framework for the program to recognize, interpret, and learn from the data.[58] Machine learning can achieve better outcomes more efficiently than human analysis of data.[59] Furthermore, it is able to accomplish increasingly complex tasks, such as pattern recognition and self-learning over time.[60]

In fact, one of the key attributes of big data outputs is its ability to scour trillions of data points and arrive at unexpected and counterintuitive conclusions.[61] The more data that is available for the computer program to analyze, the more accurate the result.[62] Predictive analytic computer programs can analyze and interpret more data more effectively than humans,[63] rendering them increasingly valuable partners to talent analytics teams.[64] Whereas humans conducting traditional talent management functions (e.g., recruiting, employee evaluations, and promotional opportunities) suffer from human cognitive biases,[65] well-designed computer programs can achieve new levels of

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56 Shen, *supra* note 32, at 52.

57 *See* WU & COGGESHALL, *supra* note 48, at vii–xiii.

58 Alexander Linden et al., *Machine Learning Drives Digital Business*, GARTNER 3 (Aug. 11, 2014); *See* KEVIN P. MURPHY, MACHINE LEARNING: A PROBABILISTIC PERSPECTIVE 1 (2012) (defining machine learning as "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty").

59 Linden, *supra* note 58, at 3 ("Machine learning models can surpass human capability in coping with significant volumes of data, finding high-order interactions and patterns within the data and dealing with highly complex business problems.").

60 *Id.* at 4; *see also* Nicola Jones, *Computer Science: The Learning Machines*, 505 NATURE 146, 147–48 (2014), http://www.nature.com/news/computer-science-the-learning-machines-1.14481 (describing Google's success at deep learning with Google Brain, which built upon prior efforts to simulate the human brain with machines).

61 Burdon & Harpur, *supra* note 2, at 694, 701.

62 *See, e.g.*, Jones, *supra* note 60, at 147 (showcasing deep data's more accurate results versus other techniques).

63 Linden et al., *supra* note 58, at 3.

64 *See* Helen Poitevin & Alexander Linden, Use Data Science to Address Employee Flight Risk, GARTNER 3–7 (2015) (describing a case study for using predictive workforce analytics to reduce employee flight risk).

65 Humans suffer from a multitude of cognitive biases. *See* Arie W. Kruglanski, *Conditions for Accuracy: General or Specific?*, *in* 68 ADVANCES IN PSYCHOLOGY: COGNITIVE BIASES 15, 28–30 (J.P. Caverni et al. eds., 1990) (providing a comprehensive overview of cognitive biases). In the context of racial employment discrimination, these human biases can be statistically appreciable. *See, e.g.*, Marianne Bertrand & Sendhil Mullainathan, *Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment On Labor Market Discrimination*, 2–3 (Nat'l Bureau of Econ. Research Working Paper

objectivity in the talent management process.[66] However, as Professor Mark Burdon notes: "The key point . . . here is that no one knows what the predictive outcome will be and whether that prediction will be valid the next day or the one after that."[67] In fact, while researchers can be tempted to change a predictive algorithm's results when they are counterintuitive, it is difficult to do so because making counterintuitive observations is one of the purposes of using a big data solution.[68] Consequently, predictive talent analytics software is extremely difficult to regulate under traditional discrimination law,[69] which requires identification of a particular business practice with a disparate impact on a protected class.[70]

The upshot of talent analytics for talent management teams is a deluge of predictive software products to improve nearly every area of corporate talent management. CEB's TalentNeuron analyzes its global data warehouse of over 5.1 billion data points related to "covering talent supply and cost" to "make smarter talent planning and recruiting decisions."[71] Lockheed Martin built a software program that aggregates individual employee performance against organizational objects and its knowledge management data to select high potential employees for "special programs" or to "monitor employees who need improvement."[72] Major software companies like IBM and Oracle have invested in predictive talent analytics, as have hot startups and established talent management software providers.[73] These market players are in-

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No. 9873, 2003), http://www.nber.org/papers/w9873.pdf (finding a fifty percent callback gap between job applicants with white-sounding names and black-sounding names with similar resumes).

66 *See, e.g.*, COLLEEN MCCUE, DATA MINING AND PREDICTIVE ANALYSIS: INTELLIGENCE GATHERING AND CRIME ANALYSIS 232 (Sara Scott ed., 2015) (stating that predictive analytics can transcend human cognitive biases in the context of crime-fighting); *but see* DANIEL M. RICE, CALCULUS OF THOUGHT: NEUROMORPHIC LOGISTIC REGRESSION IN COGNITIVE MACHINES 4–9 (2014) (arguing that the hundreds of different predictive analytics algorithms currently in use each retain the cognitive biases of the models' creators).

67 Burdon & Harpur, *supra* note 2, at 701 (footnote omitted).

68 CHARLY GORDON, BIG DATA EXCLUSIONS AND DISPARATE IMPACT: INVESTIGATING THE EXCLUSIONARY DYNAMICS OF THE BIG DATA PHENOMENON 27 (August 2014) (unpublished MSc dissertation London School of Economics and Political Science) (on file with the Department of Media and Communications, London School of Economics).

69 *See* Burdon & Harpur, *supra* note 2, at 701–05 (2014) (employing Susan Sturm's info-structural approach to discrimination to argue that the structure of big data modeling and analysis can create info-structural discrimination); *see also* Susan Sturm, *Second Generation Employment Discrimination: A Structural Approach*, 101 COLUM. L. REV. 458, 460–61 (2001) (distinguishing second-generation forms of discrimination from first generation forms).

70 *See* discussion *supra* Part I.B.1; *see also* discussion *infra* Part II.A.2.

71 *Under a New Standard in Talent Analytics*, CEB, https://www.cebglobal.com/talent-management/talent-neuron.html (last visited Aug. 21, 2016).

72 Davenport et al., *supra* note 4, at 4.

73 *See, e.g.*, Bersin, *supra* note 37 (illustrating several new talent management software vendors); *IBM Kenexa Talent Insights*, IBM, http://www-03.ibm.com/software/products/en/talent-insights (last visited Aug. 21, 2016); *Kiran Analytics Reaches Milestone of Assessing 1,000,000 Job Seekers in Quest to*

tegrating with each other to provide increasingly sophisticated talent analytics solutions.[74] The big data that such software applications analyze ranges from internal employee data to external data about prospective employees.[75] Where the data comes from, as well as how and when it is being distilled by a data model, directly impacts the ability of the FTC to regulate it under the FCRA, which deals with consumer reports being sold to third parties.[76]

Just as the data sources that feed into talent analytics software vary, the methods employed by these software solutions and their application are diverse. Infor Talent Science creates a "fit index" for job applicants to measure a candidate's "behavioral DNA" against the needs of a given job position.[77] By connecting the right applicant to the right position, one company aims to use Infor Talent Science to dramatically reduce turnover among its 6,000 employees.[78] Another software program, HireIQ, uses voice recognition to analyze behavioral characteristics in interviews to match passive candidate qualities to job positions.[79] Yet another software application claims to use statistically-validated predictive analytics on job applicant data to predict high performers.[80] Other vendors target employees post-recruitment. Cornerstone OnDemand uses employees' backgrounds and talent analytics algorithms to recommend training.[81] Workday Insights Application uses data correlations to categorize employees and determine risk of employee churn through an amalgamation of data points.[82] By acquiring Identified, Workday

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Find Top Talent for Retail Banks, KIRAN ANALYTICS, http://kiran.com/kiran-analytics-reaches-milestone-of-assessing-1000000-job-seekers-in-quest-to-find-top-talent-for-retail-banks/ (last visited Aug. 21, 2016) [hereinafter *Kiran Analytics*]; *Workforce Analytics*, PEOPLEFLUENT http://www.peoplefluent.com/products/workforce-analytics (last visited Aug. 21, 2016).

74 For example, Workday acquired a predictive startup called Identified; SAP purchased SuccessFactors, who had acquired a workforce analytics company the year before; Cornerstone purchased Evolv to connect talent data to decision-making; and LinkedIn purchased Bright.com, which uses analytics to connect job seekers' resumes to open positions. Dan Ring, *Analytics Tools Model Future for Hiring Managers, HR Software*, TECHTARGET, http://searchfinancialapplications.techtarget.com/feature/Analytics-tools-model-future-for-hiring-managers-HR-software (last visited Aug. 25, 2016).

75 *See* Press Release, Fed. Trade Comm'n, Spokeo to Pay $800,000 to Settle FTC Charges Company Allegedly Marketed Information to Employers and Recruiters in Violation of FCRA (June 12, 2012) [hereinafter FTC Press Release], https://www.ftc.gov/news-events/press-releases/2012/06/spokeo-pay-800000-settle-ftc-charges-company-allegedly-marketed (providing one example of a product that aggregated external data on a job applicant and provided it to potential employers).

76 *See* discussion *infra* Part II.B.

77 Ring, *supra* note 74.

78 *Id.* ("By the end of the first full year, approximately 70% of those are expected to take the assessments, which are not administered to applicants for all positions.").

79 Kevin G. Hegebarth, *Emotional Assessments: A Disruptive Innovation in Candidate Selection*, HIREIQ, 4–5 (2015), http://www.hireiqinc.com/wp-content/uploads/2015/12/HireIQ_-_Audiolytics_White_Paper_FINAL.pdf (last visited Aug. 21, 2015).

80 *Kiran Analytics*, *supra* note 73.

81 Ring, *supra* note 74.

82 Bersin, *supra* note 37.

took this a step further by using the predictive data to identify effective and ineffective career paths for employees, based on employee churn data.[83]

The benefits of predictive talent analytic software notwithstanding, widespread adoption of these programs carries risk to individual employees and society at large. Poorly designed or improperly deployed data models can yield inaccurate outputs,[84] inaccurate or incomplete data can contaminate results.[85] Predictive talent analytics may also have unintended and disproportionately negative impacts on certain social classes.[86] Furthermore, the legal rules for how businesses should use machine-directed recommendations have yet to be fully defined.[87] What disclosure rights should employees have when they are adversely affected by a predictive talent formula? What remedy, if any, should they be provided? What, if any, oversight should be directed towards predictive data models that affect the workforce? The following two sub-sections describe these risks; the next two sections provide an overview of applicable law.

3. Talent Analytics' Predictions Are Only as Good as Their Underlying Data

Inaccurate and incomplete datasets pose serious challenges to the effectiveness and fairness of predictive talent analytic programs that rely on large datasets to produce their recommendations.[88] Some scholars accurately described the "Big Data economy" as one "premised on the accumulation of massive amounts of data."[89] This is problematic considering the widespread

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83 *Id.*

84 Linden et al., *supra* note 58, at 10–11 (describing the risks of data models as well as the risk of data model deterioration over time).

85 *See* Barna Saha & Divesh Srivastava, *Data Quality: The Other Face of Big Data*, AT&T LABS-RESEARCH 1 (2014), https://people.cs.umass.edu/~barna/paper/ICDE-Tutorial-DQ.pdf (describing the result of widespread poor data quality and the butterfly effect for big data where "even minor errors can accumulate resulting in revenue loss, process inefficiency and failure to comply with industry and government regulations").

86 *See* Burdon & Harpur, *supra* note 2, at 694 ("Statistical discrimination is . . . discrimination by irrational correlation of information in which the discriminator bases a decision on a certain informational quality linked to the social or physical attribute of a given group."); *see also* Barocas & Selbst, *supra* note 8, at 692 (describing the discriminatory dangers of inferred rules employed in big data algorithms).

87 *See* discussion *infra* Parts I.B.2, I.C.3 (describing the challenges faced by anti-discrimination law and consumer protection law within the context of predictive talent software).

88 *See* Frank Pasquale & Danielle Keats Citron *Promoting Innovation While Preventing Discrimination: Policy Goals for the Scored Society*, 89 WASH. L. REV. 1413, 1423–24 (2014) (recommending frequent data audits for companies that hold substantial amounts of data that are used in scoring algorithms); Tal Z. Zarsky, *Understanding Discrimination in the Scored Society*, 89 WASH. L. REV. 1375, 1392–93 (2014) (describing various ways tainted datasets could impact employees when used as part of big data scoring systems); *see also* Saha & Srivastava, *supra* note 85, at 1–2.

89 Pasquale & Citron, *supra* note 88, at 1418.

data quality issues currently facing commercial enterprises.[90] By some estimates, incorrect data costs businesses $600 billion dollars annually, with a typical data error rate of one to five percent.[91]

Even where the data itself is accurate, talent management teams often possess poor data.[92] For example, data sources that rely on managerial evaluations suffer from what researchers call the Idiosyncratic Rater Effect ("IRE"), where the scores primarily reflect the impression of the reviewer rather than the performance of the employee;[93] in fact, the IRE "account[s] for over half of the variance in performance ratings."[94] Ruslan Belkin, VP of Engineering at a successful software company, describes the state of corporate data as follows: "Every single company I've worked at and talked to has the same problem without a single exception so far — poor data quality, especially tracking data . . . . Either there's incomplete data, missing tracking data, [or] duplicative tracking data."[95]

Even when the data is accurate and of high quality, successful big data projects require analytically minded teams to catch errors and ensure meaningful results, and such teams are sorely lacking in many talent management organizations.[96] Even experienced research teams can miss critical context for the underlying data, which leads to erroneous results.[97] For example, one research team attempting to predict unemployment rates in the United States based on social media set up tags such as "jobs" and "unemployment" as part of their research design.[98] After a sudden spike of social media activity, the researchers thought they were on to something and raised additional money.[99] What they did not realize is that Steve Jobs had just died, and the deluge of social media tags with the word "Jobs" skewed their study, which was designed to predict unemployment.[100]

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90 Saha & Srivastave, *supra* note 85, at 1–2.

91 *Id.* at 1.

92 Marcus Buckingham, *Most HR Data is Bad Data*, HARV. BUS. REV., Feb. 9, 2015, https://hbr.org/2015/02/most-hr-data-is-bad-data.

93 *Id.*

94 Steven E. Scullen et al., *Understanding the Latent Structure of Job Performance Ratings*, 85 J. OF APPLIED PSYCHOL. 956, 969 (2000).

95 *Everything We Wish We'd Known About Building Data Products*, FIRST ROUND REVIEW, http://firstround.com/review/everything-we-wish-wed-known-about-building-data-products/ (last visited Aug. 21, 2016) (quoting Ruslan Belkin).

96 *See Next Generation Computing Joint Hearing*, *supra* note 36, at 5 (Hearing Charter); Press Release, IBM, IBM Launches Talent Assessment to Help Aspiring Data Crunchers and Academia Gauge and Enhance Skills (Nov. 12, 2013), https://www03.ibm.com/press/us/en/pressrelease/42450.wss.

97 Linda Tucci, *Big Data Can Mean Bad Analytics, Says Harvard Professor*, TECHTARGET, http://searchcio.techtarget.com/opinion/Big-data-bad-analytics (last visited Aug. 21, 2016).

98 *Id.*

99 *Id.*

100 *Id.*

Businesses generally lack sufficient professionals with technical depth in data analytics,[101] and this is particularly true of talent management organizations.[102] In fact, talent management organizations' structure itself does not always emphasize data driven outputs,[103] because historically its focus has been on transactional human resources tasks and not analytics heavy activities.[104]

In short, excellent predictive talent analytics require data accuracy, data quality, and a qualified team of data savvy professionals; generally, these are not the characteristics of talent management teams today. The consequences of poor data for predictive analytics are well documented and implicate core questions of fairness; in the employment context, bad data can mean the difference between getting a job or a promotion and getting fired.[105] And even if predictive talent analytics gets everything right, it still risks unintentionally producing disproportionately negative impacts on certain classes of people.[106]

4. Big Data's Discriminatory Potential

The potential discriminatory impact of predictive analytics generally, and within talent management in particular, has been well documented within academic literature.[107] First, predictive formulas can create self-fulfilling

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101 *Next Generation Computing Joint Hearing*, *supra* note 36, at 4 (Hearing Charter) ("McKinsey has projected the United States will need an additional 140,000 to 190,000 professionals with significant technical depth in data analytics, and the need for an additional 1.5 million managers and analysts who can work effectively with big data analysis by 2018.") (citing James Manyika et al., *Big Data: The Next Frontier for Innovation, Competition, and Productivity*, MCKINSEY GLOBAL INSTITUTE 10 (2011), http://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Business%20Technology/Our%20Insights/Big%20data%20The%20next%20frontier%20for%20innovation/MGI_big_data_full_report.ashx).

102 CHARTERED INST. OF PERSONNEL AND DEV., TALENT ANALYTICS AND BIG DATA – THE CHALLENGE FOR HR 4–5 (Nov., 2013), https://www.oracle.com/assets/talent-analytics-and-big-data-2063584.pdf (indicating that only 21% of business leaders thought "HR draws insight from data to stimulate change and improvement in the organization").

103 Jeanne G. Harris et al., *Talent and Analytics: New Approaches, Higher ROI*, 32 J. BUS. STRATEGY 4–5 (2011).

104 Nevertheless, those talent management organizations that connect talent analytics to business outcomes correlate with successful companies. *Id.* at 6–8 (providing several case studies to promote using talent analytics for talent management).

105 *See* discussion *supra* Part I.A.2.

106 *See* discussion *supra* Part I.A.3.

107 *See, e.g.*, Burdon & Harpur, *supra* note 2, at 680; Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms* 55 B.C. L. REV. 93, 99–101 (2014); Graham Greenleaf AM, *Foreword: Abandon All Hope?*, 37 U.N.S.W. L.J. 636, 637–38 (2014); Sprague, *supra* note 3, at 35–41; Danah Boyd et al., *The Networked Nature of Algorithmic Discrimination*, OPEN TECH. INST. 54 (Oct. 2014), http://www.danah.org/papers/2014/DataDiscrimination.pdf.

prophesies against certain classes of people because of their reliance on historical data that can operate as "non-blatant proxies" for a protected class.[108] Second, classes of individuals with little-to-no digital footprint may find themselves structurally excluded from opportunities that rely on predictive data-driven decisions.[109]

One way that predictive formulas can create discriminatory effects against vulnerable classes is via class proxies.[110] In his critique of widespread scoring practices, Professor Tal Zarsky describes blatant class proxies and recommends they be prohibited from scoring practices.[111] Essentially, a data point that serves as a proxy for a class of people can functionally discriminate against that class as easily as if the class itself were being directly discriminated against.[112] For example, height and weight might serve as gender proxies, zip codes as race proxies, or food as religious proxies.[113] Non-blatant proxies can be nearly impossible to spot;[114] they emerge when there is no obvious and immediate connection between one trait and a particular class of person, but in combination with a large data set results in discriminatory outputs.[115] Professor Zarsky suggests that non-blatant proxies in scoring formulas create disparate impacts on certain classes, and that these disparate effects can already be seen in cases involving lenders and insurance companies.[116]

Big data and predictive analytics compound the difficulty described above. Whereas blatant proxies might be banned, as Professor Zarsky suggests, predictive analytics look at billions of non-blatant data points and are constantly learning and changing via the process of machine learning.[117] Furthermore, the predictions and prescriptions produced by the program constantly change, making it difficult to determine potentially discriminatory proxies.[118] To illustrate the difficulty posed by machine-learning algorithms, consider the example of race and online advertisements. One study indicated that using Google search algorithms to search a "black-identifying name was

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108 Crawford & Schultz, *supra* note 107, at 100–01; Zarsky, *supra* note 88, at 1389–90.

109 *See* Boyd et al., *supra* note 107, at 54–55.

110 Crawford & Schultz, *supra* note 107, at 100–01; Zarsky, *supra* note 88, at 1389–92.

111 Zarsky, *supra* note 88, at 1394–96. Although this article was focused on scoring practices (e.g., credit scoring, etc.) in general and not big data in particular, the analysis remains relevant to this analysis.

112 *Id.* at 1395.

113 *Id.* at 1394–95.

114 *Id.* at 1392–93.

115 *Id.*

116 Zarsky, *supra* note 88, at 1396 & 1396 n.100.

117 MURPHY, *supra* note 58, at 2.

118 *See* Burdon & Harpur, *supra* note 2, at 701–02 (citing Crawford & Schultz, supra note 107, at 106–07).

[twenty-five percent] more likely to get an ad suggestive of an arrest record."[119] In response, a Google spokesperson stated, "AdWords does not conduct any racial profiling."[120] This is precisely the difficulty—algorithms drawing correlations between billions of seemingly non-discriminatory data points and producing adverse discriminatory effects.[121]

In the case of predictive talent analytics, people's jobs and future lives are at stake. Furthermore, in the absence of overt indicators of racism, which are available for many online searches,[122] it may prove nearly impossible to prove a case of discrimination for predictive analytics in the employment context.[123] One scholar concluded that data mining within the workplace "may reflect the quintessential unintentional discrimination . . . ."[124] Another reasoned that "[d]iscrimination may be an artifact of the data mining process itself, rather than a result of programmers assigning certain factors inappropriate weight."[125] Other literature points to the absence of certain data as causative of exclusionary results within the big data context.[126]

In sum, predictive talent analytics risks subtle discrimination against employees that may be difficult to discern and challenging to regulate. Unlike some forms of human discrimination, algorithmic discrimination lacks discriminatory animus.[127] Rather, it is the unintended result of a predictive data model crunching billions of data points.[128]

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119 Latanya Sweeny, *Discrimination in Online Ad Delivery*, 56 COMM. ACM 44, 51 (May 2013).

120 *Racism is Poisoning Online Ad Delivery, Says Harvard Professor*, MIT TECH. REV. (Feb. 4, 2013), http://www.technologyreview.com/view/510646/racism-is-poisoning-online-ad-delivery-says-harvard-professor/.

121 Samuel Gibbs, *Google Says Sorry Over Racist Google Maps White House Search Results*, THE GUARDIAN (May 20, 2015), http://www.theguardian.com/technology/2015/may/20/google-apologises-racist-google-maps-white-house-search-results (describing "[the] systems [as] automated, taking user input from the billions of searches performed using Google to predict likely queries and results.").

122 *See, e.g.*, Alex Hern, *Flickr Faces Complaints Over 'Offensive' Auto-Tagging for Photos*, GUARDIAN (May 20, 2015), http://www.theguardian.com/technology/2015/may/20/flickr-complaints-offensive-auto-tagging-photos (describing Flickr's auto-tagging feature that was designed to tag posted photos using "advanced image recognition technology," but a portrait of a black man was auto-tagged as "animal" and "ape").

123 *See* GORDON, *supra* note 68, at 27–28 ("Many interviewees underlined the difficulty in establishing methods of algorithmic oversight in the case of Big Data analytics. 'Who really understands how they work[,]' asked M.L. 'There are just a handful of people who really know how they function and with the development of machine learning, nobody understands what's really going on, not even the developers.'").

124 Sprague, *supra* note 3, at 38.

125 Barocas & Selbst, *supra* note 8, at 674.

126 Boyd et al., *supra* note 107 (describing how candidate filtering software computationally excludes people for *not* having certain things).

127 Barocas & Selbst, *supra* note 8, at 674 ("Because the discrimination at issue is unintentional, even honest attempts to certify the absence of prejudice on the part of those involved in the data mining process may wrongly confer the imprimatur of impartiality on the resulting decisions").

128 *Id.*

B. *Title VII Employee Protections and Technology Regulations*

The previous section established both the inevitability and potential benefit of predictive talent analytics as well as its inherent dangers with respect to fairness and discriminatory effects. This section describes one of the two primary sources of regulation, Title VII, and the process by which a disparate impact claim is made. This sets the stage for analysis of a hypothetical disparate impact claim involving predictive talent analytics in Part II.

1. History and Types of Title VII Actions[129]

Title VII of the Civil Rights Act bans workplace discrimination based on several protected characteristics.[130] Since its initial enactment, succeeding amendments and court rulings have expanded its scope and strengthened its enforcement.[131] The Supreme Court first recognized the broader application of the 1964 Act as compared to its 1875 predecessor by holding that it applied to private sector discrimination.[132] Subsequent amendments broadened the scope of the Title VII to include discrimination of other protected classes (e.g., gender) and empowered the EEOC to conduct its own enforcement litigation to implement the statute.[133]

There are two types of discrimination actions recognized under Title VII: (1) disparate treatment of persons based on a protected characteristic,[134] and (2) employment practices that result in an adverse disparate impact on

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129 While this paper focuses on the Title VII and the CRA, it is important to note that other similar legislation was modeled from the CRA, such as the Americans with Disabilities Act of 1990, the Voting Rights Act of 1965 and the Civil Rights Act of 1968, which expanded civil rights acts to other groups. Other sources of law related to employment discrimination are: Equal Pay Act of 1963 ("EPA"), Age Discrimination in Employment Act of 1967 ("ADEA"), Titles I and V of the Americans with Disabilities Act of 1990 ("ADA"), Sections 501 and 505 of the Rehabilitation Act of 1973, and the Civil Rights Act of 1991. However, the basic framework applied under Title VII analysis is applied by the EEOC in enforcement of all antidiscrimination acts.

130 Civil Rights Act of 1964, Pub. L. No. 88-352, §703(a)(1), 78 Stat. 241, 255 (codified as amended at 42 U.S.C. § 2000e-2(a)(1) (2012) ("It shall be an unlawful employment practice . . . to fail or refuse to hire or to discharge any individual, or otherwise to discriminate against any individual . . . because of such individual's race, color, religion, sex, or national origin . . .")).

131 *See The Law*, EQUAL EMP'T OPPORTUNITY COMM'N, http://www.eeoc.gov/eeoc/history/35th/thelaw/ (last visited Aug. 21, 2016) (summarizing laws currently enforced by EEOC) [hereinafter *EEOC Law Summary*].

132 Heart of Atlanta Motel, Inc. v. United States, 379 U.S. 241, 261 (1964) (upholding application of the CRA to the private sector); *see also* Susan Melanie Jones, Note, *Applying Disparate Impact Theory to Subjective Employee Selection Procedures*, 20 LOY. L. A. L. REV. 375, 376–77 (1987).

133 *See generally EEOC Law Summary*, *supra* note 131.

134 *See* Tex. Dep't of Cmty. Affairs v. Burdine, 450 U.S. 248, 253–54 (1981); McDonnell Douglas Corp. v. Green, 411 U.S. 792, 802 (1973).

persons within a protected class.[135] The following takes each in turn and provides illustrative examples of disparate impact claims with respect to employment tests, which may be used analogously to predictive talent analytics software in certain respects.[136]

a. *Disparate Treatment*

Generally, courts use a three-part analytical framework when evaluating disparate treatment claims.[137] First, the court evaluates whether or not a plaintiff made a prima facie case of discriminatory treatment.[138] If so, the court determines whether the employer can show that it possessed a legitimate, nondiscriminatory reason for its employment policy.[139] If the employer cannot make an adequate showing then it is liable for discrimination; if it can make an adequate showing, then the burden shifts to the plaintiff to show that the employer's proffered purpose is not the true reason for the adverse employment decision.[140]

b. *Disparate Impact*

When conducting disparate impact analyses, courts ask if a particular employment practice (1) creates a statistically validated disparate impact on a protected minority that (2) is not justified by a legitimate business interest (the "business necessity exception").[141] If a business proves a business necessity for the employment practice in question, the burden shifts to the plaintiff

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135 *See* Tex. Dept. of Hous. & Cmty. Affairs v. Inclusive Cmty. Project, Inc., 135 S. Ct. 2507, 2526–27 (2015) (Thomas, J., dissenting) (critiquing the Court's recent validation of disparate *impact* under *Griggs v. Duke Power Co.*, 401 U.S. 424 (1971), and advocating instead for an interpretation of Title VII that only recognizes disparate *treatment*).

136 In a way, employment testing collects data about a candidate and predicts future performance based on the results.

137 *Burdine*, 450 U.S. at 252–53 (describing the basic burden shifting scheme for disparate treatment cases); *McDonnell Douglas*, 411 U.S. at 802.

138 *Burdine*, 450 U.S. at 254 (stating that the "burden of establishing a prima facie case of disparate treatment is not onerous. The plaintiff must prove . . . that she applied for an available position for which she was qualified, but was rejected under circumstances which give rise to an inference of unlawful discrimination." (citing *McDonnell Douglas*, 411 U.S. at 802)).

139 *Id.* at 254–55. In cases of facially discriminatory policies, businesses have a high burden to prove a legitimate reason for the policy. *See, e.g.*, Int'l Union v. Johnson Controls, Inc., 499 U.S. 187, 198 (1991) (applying the bona fide occupational requirement defense to Johnson Controls' facially discriminatory employment practice and disallowing application of the business necessity defense, which is applicable only in disparate impact cases).

140 *See Burdine*, 450 U.S. at 256.

141 42 U.S.C § 2000e–2(k)(1)(A)(i) (2012); *see, e.g.*, Griggs v. Duke Power Co., 401 U.S. 424, 436 (1971) (validating the EEOC's interpretation of Title VII, which required employment tests to be job

to demonstrate an equally valid, less discriminatory means of achieving the business interest.[142]

The EEOC has used a variety of techniques to establish the first element. One technique, the Eighty Percent Rule,[143] was codified in the 1978 Uniform Guidelines on Employee Selection Procedures,[144] which is used by the EEOC when litigating disparate impact claims.[145] The Eighty Percent Rule determines the percentage of job applicants hired or promoted by an employer that falls within a protected class and compares it to the percentage of job applicants outside the protected class who are promoted or hired.[146] For example, if a company hires thirty percent of qualified black job applicants and sixty percent of white applicants, the company could be forced to prove it has a business necessity defense under the Eighty Percent Rule.[147] It is worth noting that while the EEOC considers the Eighty Percent Rule a good rule of thumb, it recognizes that there are alternatives to the Eighty Percent Rule in certain scenarios.[148] For example, Section 4d of the Uniform Guidelines on Employee Selection Procedures opens the door to consider the practical impacts of hiring practices that affect a small population rather than strictly applying the Eighty Percent Rule.[149]

Plaintiffs often have difficulty making their prima facie case, even prior to considering a defense under the business necessity exception. Not only must plaintiffs marshal valid statistical evidence to make their case, they

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related so that a person is measured "for the job and not the person in the abstract"); *see also* Michael Selmi, *Was the Disparate Impact Theory a Mistake?*, 53 UCLA L. REV. 701, 702–08 (2006) (providing an excellent overview and critique of the disparate impact theory).

142 42 U.S.C §§ 2000e–2(k)(1)(A)(ii) and (C) (2012); *see, e.g.*, Ricci v. DeStefano, 557 U.S. 557, 589–91 (2009) (analyzing the various alternatives proffered by the plaintiff and finding that plaintiffs did not show a reasonable alternative that would have resulted in a reduced racial impact).

143 *Uniform Guidelines on Employee Selection Procedures Questions & Answers*, U.S. EQUAL OPPORTUNITY EMP. COMM'N, http://www.uniformguidelines.com/uniformguidelines.html (last visited Aug. 21, 2016) ("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, while a greater than four-fifths rate will generally not be regarded by Federal enforcement agencies as evidence of adverse impact.").

144 *See* 29 C.F.R. § 1607.4D (1987).

145 DAN BIDDLE, ADVERSE IMPACT AND TEST VALIDATION: A PRACTITIONER'S GUIDE TO VALID AND DEFENSIBLE EMPLOYMENT TESTING 2–6 (2006) (providing a brief history culminating in the Eighty Percent Rule and describing its application, which also requires statistical significance levels where the p-value is at least .05).

146 *Id.* at 3–4.

147 In this scenario, the hiring percentage is fifty percent and falls below the required eighty percent (30/60*100 = 50%); *see, e.g.*, *Ricci*, 557 U.S. at 586–87 (finding a prima facie case of disparate impact where white candidates had a 64% exam pass rate and black and Hispanic candidates had a 37.5% pass rate).

148 29 C.F.R. § 1607.1(b) (2015).

149 29 C.F.R. § 1607.4D (2015) ("Smaller differences in selection rate may nevertheless constitute adverse impact, where they are significant in both statistical and practical terms or where a user's actions have discouraged applicants disproportionately on grounds of race, sex, or ethnic group.").

must also point to a tangible business practice that generated the disparate impact.[150] While clear in some cases (e.g., standardized tests for employment where pass/fail rates can be measured), it can be very difficult to identify problematic business practices in others.[151] Moreover, because the judiciary is acutely aware of the negative impact that abusive disparate impact claims might have on businesses, it requires "robust causality" to be proven by statistical evidence.[152] If the court finds the plaintiff has fulfilled step one, courts turn to step two: the business necessity defense.[153]

Although the mechanics of the business necessity defense are straightforward, its application has proven to be less clear. In order to prove a business practice is necessary, an employer must show the practice is job-related for the position in question and consistent with a business necessity.[154] It is not sufficient for the outcome of the employment practice to be racially neutral;[155] it is necessary that the component parts also pass the disparate impact test.[156] When evaluating the business necessity of employment tests, courts have held that facially neutral tests that are related to job performance but have an adverse disparate impact on a protected class are permissible under Title VII.[157] In some cases, however, the Supreme Court has critiqued the

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150 Meacham v. Knolls Atomic Power Lab., 554 U.S. 84, 100 (2008) ("[A] plaintiff falls short by merely alleging a disparate impact, . . . The plaintiff is obliged to do more: to 'isolat[e] and identif[y] the *specific* employment practices that are allegedly responsible for any observed statistical disparities.'" (quoting Smith v. City of Jackson, Miss., 544 U.S. 228, 241 (2005)) (recognizing that the employer bears the burden of persuasion to show the reasonableness defense of its business practice in ADEA claims, but balancing that burden with a high standard for plaintiff's prima facie case).

151 *See, e.g.*, Wal-Mart Stores, Inc. v. Dukes, 131 S. Ct. 2541, 2552 (2011) (holding that "[i]n this case, proof of commonality necessarily overlaps with respondents' merits contention that Wal-Mart engages in a *pattern or practice* of discrimination. . . . "[w]ithout some glue holding the alleged reasons for all those decisions together, it will be impossible to say that examination of all the class members' claims for relief will produce a common answer to the crucial question *why was I disfavored*.") (footnote omitted).

152 *See, e.g.*, Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmty. Project, 135 S. Ct. 2507, 2512, 2524 (2015) ("If the specter of disparate-impact litigation causes private developers to no longer construct or renovate housing units for low-income individuals, then the FHA would have undermined its own purpose as well as the free-market system.").

153 42 U.S.C. § 2000e-2(k)(1)(A)(i) (2012).

154 42 U.S.C. §§ 2000e-2(k)(1)(A)(B) (2012).

155 *See* Connecticut v. Teal, 457 U.S. 440, 451 (1982).

156 *See, e.g.*, *id.* at 452 (holding a test used for promotions that had a disparate impact violated Title VII even where the bottom line result of the promotional system resulted in an appropriate racial balance).

157 *See* Ricci v. DeStafano, 557 U.S. 557, 592–93 (2009) (finding a test that was designed to be racially neutral permissible under a disparate impact scheme, despite a disparate impact due to business necessity); *see also Inclusive Cmty. Project*, 135 S. Ct. at 2511 (finding that a plaintiff must show an available and less discriminatory alternative before a court can reject a defendant's valid business justification).

underlying proof of employment tests to invalidate the business necessity defense.[158] In *Albermarle Paper Co. v. Moody*,[159] the Court deferred to EEOC administrative guidelines to invalidate a paper company's employment test.[160] The Court found that, under the guidelines, a test must be "predictive of or significantly correlated with important elements of work behavior which comprise or are relevant to the job or jobs for which candidates are being evaluated."[161] By that standard, the Court found the paper company's validation study materially defective because (1) the correlation was not strong enough; (2) the subjective evaluation portions were too vague; (3) it focused on job groups near the top of career progression lines; (4) and it was administered only to experienced, white workers whereas the actual test was administered to many younger, nonwhite workers.[162] Given the EEOC's history of enforcing Title VII in the context of employer examination data, it is no surprise that it has taken an interest in big data.

2. The EEOC's Current Application of Title VII to Talent Analytics

The White House, EEOC, and FTC have indicated that big data within the employment context will become a growing priority for the Federal government.[163] For its part, the EEOC appears to be taking a straight-forward approach to regulating predictive talent analytics under Title VII.[164] The EEOC's Assistant General identified prejudices built into big data as key to determining the legality of applicant screening, but underscored that only those practices that are "not job related and consistent with business necessity" would be impermissible under Title VII.[165] She particularly warned against using social media as part of employee screening processes due to the amount of information available on social media concerning protected classes.[166] Nevertheless, she indicated that data tools which do accurately predict

158 *See* Albermarle Paper Co. v. Moody, 422 U.S. 405, 435–36 (1975).
159 422 U.S. 405 (1975).
160 *Id.* at 431.
161 *Id.* (internal quotations omitted).
162 *Id.* at 431–36.
163 *See* Statement of Carol Miaskoff, Transcript, FTC Big Data: A Tool for Inclusion or Exclusion (Sept. 15, 2014) [hereinafter Miaskoff Statement], https://www.ftc.gov/system/files/documents/videos/big-data-tool-inclusion-or-exclusion-part-5/ftc_big_data_workshop_-_transcript_segment_5.pdf; *see also*, Ryan O'Leary & Brian O'Leary, *Legal Watch*, INT'L PERS. ASSESSMENT COUNCIL 10 (Jan. 2015), http://www.ipacweb.org/Resources/Documents/acn/acn_1501.pdf ("Several recent Federal government activities have shown an increased concern over the use of big data. In May, the White House issued a report . . . which detailed the results of a 90-day study examining how big data will transform the way we live and work, . . . A significant finding of the report was that big data analytics have the potential to eclipse longstanding civil rights protections . . . .").
164 Miaskoff Statement, *supra* note 163.
165 *Id.*
166 *Id.*

job performance are permissible.[167] But how will the EEOC evaluate whether or not predictive talent analytics, which relies on big data, sufficiently predicts job performance?[168] The answer to that question, as explored in Part II, may prove prohibitively difficult to answer.

C. *FTC Employee Protections, Technology*

Whereas Title VII protects employees from discrimination, the FCRA protects consumers from exploitation by unfair business practices.[169] The FCRA was originally enacted in 1970 as an amendment to the Consumer Credit Protection Act with the express purposes of requiring banks to maintain certain records.[170] Today, the Act includes disclosure requirements on the part of consumer reporting agencies as well as on employers using a consumer report for employment purposes.[171] This section overviews (1) the broadened application of the FCRA and (2) how the FCRA is currently applied to places of employment.

1. The Broad Role of the FCRA

Belying its name, the FCRA regulates far more than traditional credit reports.[172] The terms of the act are defined broadly, permitting consumer reports to be disseminated if the consumer reporting agency has reason to believe the information will be used for employment purposes, if there is a legitimate business need for the information, or for investigative purposes.[173] The Act itself defines a "consumer" as any "individual."[174] It defines a consumer report as:

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167 Allison Grande, *Use 'Big Data' With Caution, EEOC Counsel Urges Employers*, LAW360 (Sep. 15, 2014), http://www.law360.com/articles/577390/use-big-data-with-caution-eeoc-counsel-urges-employers (reporting on EEOC statements indicating that the data tool would only be prohibited "if it doesn't accurately predict the success of an individual at a job").

168 As has been previously discussed, big data analytics generates dynamic and constantly changing results which only a handful of highly technical individuals may understand. *See* GORDON, *supra* note 68, at 27.

169 15 USC § 1681 (2012).

170 *See* FTC, 40 YEARS OF EXPERIENCE, *supra* note 7, at 1–3, 19.

171 *See id.* at 64, 70, 74.

172 Teresa L. Butler, *The FCRA and Workplace Investigations*, 15 LAB. LAW. 391, 392 (2000) ("Despite the 1996 amendments, the Act's title is still commonly misinterpreted to cover only credit reports. The Act's provisions actually apply to 'consumer reports' and 'investigative consumer reports' that may contain absolutely no credit-related information.") (footnote omitted).

173 15 U.S.C. § 1681b (2012).

174 15 U.S.C, § 1681a(c) (2012).

> [A]ny written, oral, or other communication of any information by a consumer reporting agency bearing on a consumer's credit worthiness, . . . character, general reputation, personal characteristics, or mode of living which is used or expected to be used or collected in whole or in part for the purpose of serving as a factor in establishing the consumer's eligibility for . . . employment purposes; or any other purpose authorized under section 1681b of this title.[175]

Finally, "consumer reporting agency" refers to any person who "regularly engages in whole or in part in the practice of assembling or evaluating consumer credit information or other information on consumers for the purpose of furnishing consumer reports to third parties."[176]

Taken together, these terms encompass a lot: target marketing lists have been considered consumer reports, as have credit reports used in insurance claims.[177] In one instance, the Fifth Circuit held that a drug test from a laboratory would have been a consumer report had such tests been regularly furnished by the laboratory.[178] In *Trans Union Corp. v. FTC*,[179] the court highlighted the broad definition of a consumer report, stating that "almost any information about consumers arguably bears on their personal characteristics or mode of living."[180]

On the other hand, the boundaries of the FCRA are not limitless.[181] Retailers (or other creditors) that merely report buyer information to credit reporting agencies do not fall under the FCRA.[182] The Act does not "impose obligations upon a creditor who merely passes along information concerning particular debts owed to it."[183] This is particularly important to the consideration of predictive talent analytics software, where "consumer" information is being aggregated for employment purposes, because it limits the FTC's

175 15 U.S.C. § 1681a(d)(1) (2012). Section 1681b explicitly permits disclosure of consumer reports if the intended use of the information is for employment purposes.

176 15 U.S.C. § 1681a(f) (2012).

177 *See* Trans Union, LLC v. FTC, 536 U.S. 915, 915 (2002) (Kennedy, J., dissenting) (petition for certiorari) ("In 1994, the [FTC] issued a decision holding that the information communicated by petitioner's target marketing lists were 'consumer reports,' the sale of which is prohibited by the Fair Credit Reporting Act . . . ."); Yang v. Gov't Emps. Ins., 146 F.3d 1320, 1325 (11th Cir. 1998) (finding a report assembled as part of an insurance claim to constitute a consumer report under the FCRA).

178 Hodge v. Texaco, Inc., 975 F.2d 1093, 1097 (5th Cir. 1992).

179 245 F.3d 809 (D.C. Cir. 2001).

180 *Id.* at 813.

181 The FCRA includes several exclusions to its definition of consumer reports, including: "report[s] containing information solely as to transactions or experiences between the consumer and the person making the report; communication of that information . . . affiliated by corporate control; or communication . . . among persons related by common ownership . . . ." 15 U.S.C. § 1681a(d)(2)(A) (2012).

182 *See* Rush v. Macy's New York, Inc., 775 F.2d 1554, 1557 (11th Cir. 1985) (concluding that Macy's was not a CRA nor was a report concerning its direct experiences with a customer a consumer report under the FCRA).

183 DiGianni v. Stern's, 26 F.3d 346, 348–49 (2nd Cir. 1994) (concluding that retailers "that merely furnish information to [CRAs] based on their experience with consumers are not [CRAs]").

statutory ability to regulate talent analytics under the FCRA.[184] For example, LinkedIn's Reference Search feature defeated a challenge under the FCRA because the software feature fell under the Act's transaction and experiences exception.[185] Essentially, a company's direct experiences or transactions with a consumer do not in themselves constitute a consumer report under the Act.[186] The court held that LinkedIn's feature merely enabled a prospective employer to directly conduct a reference check, which is permitted under the FCRA, and did not aggregate any additional consumer information necessary to take it outside of the direct experiences exception.[187] Although the experiences and transactions exception typically applies to direct interactions between two parties, in this case, the court reasoned that LinkedIn users had provided their information to LinkedIn with the purpose of having it posted.[188] Thus, the court held that LinkedIn was not a CRA, nor did Reference Search furnish consumer reports as defined under the FCRA.[189]

2. Information Providers, Consumer Reporting Agencies, and Employer Requirements

The FCRA imposes requirements on individuals that provide CRAs with consumer information, as well as upon CRAs and employers using consumer reports furnished by CRAs.[190] Understanding these requirements proves critical to determine what, if any, software can currently be regulated under the FCRA and to developing a statutory interpretation that broadens the application of the statute. The following describes each in turn.

a. Individuals That Provide CRAs with Consumer Information

Persons or businesses that furnish consumer information to CRAs cannot do so if they "know[] or [have] reasonable cause to believe that the information is inaccurate."[191] Furthermore, "reasonable cause" in Section

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184 *See, e.g.*, Sweet v. LinkedIn Corp., No. 5:14-cv-04531-PSG, 2015 WL 1744254, at *6 (N.D. Cal. Apr. 4, 2015).

185 *Id.* at *4.

186 *Id.* at *5; *see also* FTC, 40 YEARS OF EXPERIENCE, *supra* note 7, at 24.

187 *Sweet,* 2015 WL 1744254, at *6 ("Equally misplaced is Plaintiffs' claim that the Reference Searches' inclusion of information about the listed references takes LinkedIn's publication of subjects' employment histories outside the exception.").

188 *Id.* at *6 (distinguishing the case from *Robins v. Spokeo, Inc.* because "the subjects of the Reference Searches voluntarily provide their names and employment histories to LinkedIn for the purpose of publication").

189 *Id.* at *9–10.

190 *See generally*, FTC, 40 YEARS OF EXPERIENCE, *supra* note 7.

191 15 U.S.C. § 1681s-2(a)(1)(A) (2012).

623(a)(1)(D) of the FCRA only refers to "having specific knowledge, other than solely allegations by the consumer, that would cause a reasonable person to have substantial doubts about the accuracy of the information."[192] Thus, general statistics where data quality is poor and inaccurately interpreted by predictive talent analytics products would not appear to pass the "specific knowledge" definition unless the inaccuracies were specifically known.[193]

The FCRA includes notice requirements for financial institutions providing consumer data to CRAs, but omits non-financial institutions from those requirements.[194] The FCRA requires a financial institution that (1) "extends credit," (2) "regularly . . . furnishes information to a consumer reporting agency," and (3) "furnishes negative information" to provide notice to the consumer.[195] The FCRA include timelines for notices to be provided, content requirements for notices, opportunity for the consumer to contest the information, as well as model notices to assist businesses and protections against frivolous disputes.[196] However, data provided by non-financial institutions with respect to talent analytics products would not fall under the notice requirements of section 623(a) for furnishers of information to CRAs.

b. CRA and Employer Requirements When Furnishing Consumer Reports for Employment Purposes

The FCRA generally permits CRAs to furnish consumer reports to anyone that "intends to use the information for employment purposes," or has an "otherwise legitimate business need."[197] However, the FCRA imposes certain requirements on CRAs and consumer report recipients when the reports are used in an employment context.[198] The recipient of a consumer report in the employment context must certify to the CRA that it is in compliance with the requirements of the FCRA.[199] This requirement enables the FTC to more effectively police CRAs' distribution of consumer reports.[200] Specifically, the

192 15 U.S.C. § 1681s-2(a)(1)(D) (2012).

193 *See* Saha & Srivastava, *supra* note 85.

194 *In Brief: The Financial Privacy Requirements of the Gramm-Leach-Bliley Act*, FED. TRADE COMM'N, https://www.ftc.gov/tips-advice/business-center/guidance/brief-financial-privacy-requirements-gramm-leach-bliley-act (last visited Aug. 21, 2016).

195 15 U.S.C. § 1681s-2(a)(7)(A)(i) (2012) ("If any financial institution that extends credit and regularly . . . furnishes information to a [CRA] described in section 1681a(p) of this title furnishes negative information to such an agency regarding credit extended to a customer, the financial institution shall provide a notice of such furnishing of negative information, in writing, to the customer.").

196 15 U.S.C. § 1681s-2(a)(7)(B) (2012). Employment purpose, when used in connection with a consumer report, is defined as "a report used for the purpose of evaluating a consumer for employment, promotion, reassignment or retention as an employee." 15 U.S.C. § 1681a(h) (2012).

197 15 U.S.C. § 1681b(a)(3)(B) and (F) (2012).

198 15 U.S.C. § 1681b(b)(1) (2012) (requiring certification from the report's user).

199 *Id.*

200 *See* Complaint at 6, United States v. Spokeo, No. CV12-05001 (C.D. Cal. Jun. 7, 2012).

FCRA requires that recipients of consumer reports disclose receipt of the report to consumers, though disclosure requirements have a lower standard for consumers in the job application process.[201]

When taking an adverse employment action against a consumer (typically an employee) on the basis of a consumer report, the employee must be provided a copy of the report as well as a description of his or her rights as a consumer.[202] In cases where the adverse action is taken against a person *applying* for employment, prospective employers must provide notice of the adverse action to the applicant and direct them to the CRA, which, in turn must provide the applicant a copy of the report upon request.[203] The employer need not explain which parts of the report adversely impacted the applicant, but the CRA must provide the applicant with the opportunity to contest the accuracy of the report's contents.[204] Furthermore, even in cases where the CRA compiles only information that is in the public record, notice must be provided to the consumer.[205]

c. FTC Enforcement Authority: Rulemaking and Adjudication

The FCRA authorizes the FTC to enforce its provisions under the authority of the FTCA by requiring that any violations of the FCRA provisions be considered an "unfair or deceptive act or practice in commerce" and, thus, a violation of Section 5(a) of FTCA.[206] The FCRA explicitly authorizes enforcement of the Act with the full power of the FTCA,[207] "as though the applicable terms and conditions of the [FTCA] were part of this subchapter."[208]

The FTCA, for its part, affords the FTC rulemaking power to prescribe "rules which define with specificity acts or practices which are unfair or deceptive acts or practices in or affecting commerce" within Section 5 of the FTCA.[209] The FTC possesses "hybrid" rulemaking power, which means that

201 15 U.S.C. § 1681b(b)(2)(A) and (B) (2012) ("If a consumer described in subparagraph (C) applies for employment . . . the person who procures the consumer report on the consumer for employment purposes shall provide to the consumer, by oral, written, or electronic means, notice that a consumer report may be obtained for employment purposes, and a summary of the consumer's rights . . . .").

202 15 U.S.C. §§ 6181b(b)(3)(A), 6181m(a)(1) (2012).

203 15 U.S.C. § 1681b(b)(3)(B) (2012); FTC, 40 YEARS OF EXPERIENCE, *supra* note 7, at 14.

204 15 U.S.C. § 1681b(b)(3)(B)(i) (2012).

205 15 U.S.C. § 1681k(a) (2012).

206 15 U.S.C. § 1681s(a)(1) (2012).

207 Although the Dodd-Frank Act moved several areas of enforcement to the CFPA, the FTC retained its general enforcement powers. Andrew M. Smith & Peter Gilbert, *Fair Credit Reporting Act Update—2011*, 67 BUS. LAW. 585, 586 (2012) ("[T]he CFPA amended the FCRA to provide the CFPB with general enforcement powers 'with respect to any person subject to this title,' but the FTC continues to maintain its general enforcement jurisdiction under the FCRA as well." (quoting 15 U.S.C. § 1681s(a) (Supp. IV 2010)).

208 15 U.S.C. § 1681s(a)(1) (2012).

209 15 U.S.C. § 57a(a)(1)(B) (2012).

the FTC must follow certain procedures to ensure sufficient fact finding and public comment when exercising its formal rulemaking powers.[210] As an alternative to formal rulemaking, the FTC can regulate an industry via adjudication; for example, the FTC has shown a willingness regulate cybersecurity using its adjudication authority.[211]

Regulation via adjudication means establishing rules by strategically bringing claims in particular cases through administrative complaints or litigation and establishing baseline rules on a case-by-case basis.[212] The FTC historically uses both adjudication and rulemaking to enforce its Section 5 powers.[213] When determining whether to use rulemaking or adjudication to address a potentially unfair or deceptive act, the FTC considers (1) the prevalence of acts under investigation, (2) the cost of rulemaking proceedings, and (3) feasibility of enforcement by the FTC.[214] If the undesired acts are prevalent, the cost of formal rulemaking reasonable, and the area is something that the FTC can reasonably enforce, then it is a candidate for formal rulemaking.

Due to historical factors, the FTC has been cautious with the exercise of its rulemaking powers, but it has recently shown an increased willingness to regulate the data space using its adjudicative authority.[215] This is particularly true with respect to cybersecurity and data protection policies.[216] In a recent

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210 *See* VANESSA K. BURROWS & TODD GARVEY, CONG. RESEARCH SERV. R41546, A BRIEF OVERVIEW OF RULEMAKING AND JUDICIAL REVIEW 3–4 (2011); CTR. FOR REG. EFFECTIVENESS, PART 1: OVERVIEW OF FED. AGENCY RULEMAKING 15, http://www.thecre.com/forum2/wp-content/uploads/2015/09/ABA-Rulemaking.pdf (last visited Aug. 21, 2016) [hereinafter OVERVIEW OF FED. AGENCY RULEMAKING] (describing common hybrid rulemaking requirements "such as requirements for informal public hearings, cross-examination of witnesses, more extensive statements of justification for proposed and final rules, or the application of the 'substantial evidence' test to court review of agency rules") (footnotes omitted). *But see*, ADMIN. CONF. OF THE U.S., HYBRID RULEMAKING PROC. OF THE FED. TRADE COMM'N 9 (June, 1979) (critiquing the efficacy of hybrid rulemaking under the FTCA).

211 Robert A. Schwinger & Neal J. McLaughlin, *FTC Held to Have Authority to Regulate Cybersecurity Practices under Section 5 of the FTC Act*, PRATT'S PRIVACY & CYBERSECURITY LAW REPORT 17 (Jan. 2016).

212 Mary L. Azcuenaga, FTC Commissioner, FTC Rulemaking: Harnessing Fire, Address before the Society of Consumer Affairs Professionals in Business SOCAP Meeting 2–5 (Sept. 12, 1985).

213 *See generally* Charles H. Koch, Jr. & Beth Martin, *FTC Rulemaking Through Negotiation*, 61 N.C. L. REV. 275, 278–301 (1983).

214 FED. TRADE COMM'N, OM RELEASE 89-1, OPERATING MANUAL 3, https://www.ftc.gov/sites/default/files/attachments/ftc-administrative-staff-manuals/ch07rulemaking.pdf (last visited Aug. 21, 2016).

215 *See, e.g.*, Azcuenaga, *supra* note 212, at 1 ("Only a few years ago, the FTC's rulemaking activity was a subject of considerable controversy. One particularly famous –or infamous—FTC rulemaking was the . . . 'Kid Vid' rule. The Kid Vid proposal—which would have limited or even eliminated television advertising directed at children because it was allegedly unfair—was severely criticized as an attempt to engage in social engineering that went far beyond the FTC's legitimate regulator[y] authority.").

216 *See* Dennis Hirsch, *Unfair! Or Is It? Big Data and the FTC's Unfairness Jurisdiction*, WESTIN RES. CTR. (Jul. 31, 2014), https://iapp.org/news/a/unfair-or-is-it-big-data-and-the-ftcs-unfairness-juris

case, the FTC aimed its adjudication powers to regulate proper data protection practices at businesses holding consumer data.[217]

3. FTC's Inconsistent Application of the FCRA to Talent Software

The FTC appears to consider talent analytics software itself as beyond its regulatory authority.[218] But when a company uses a talent analytics software product to generate reports that it sends to third parties, then those reports can be regulated under the FCRA as consumer reports. The FTC interprets the FCRA to exclude talent analytics software and their respective software providers from its definition of consumer reports and CRAs, respectively.[219] In its comprehensive 2011 guidance on the FCRA, the FTC indicated that software platforms are not consumer reports because they, in themselves, do not constitute a report with consumer information.[220] Furthermore, the companies that provide software that enables their customers to assemble reports are not themselves CRAs because "that task itself is not 'assembling or evaluating' the information is thus not a CRA."[221] However, companies that sell "merge and purge reports" from a CRA "is itself a CRA."[222]

Thus, in one example of FTC adjudicative action of big data talent analytics, it fined Spokeo for using its software product to mine millions of data points available on the web, repackaging the data into profiles, and reselling the data to corporate talent management clients.[223] By contrast, the FTCs attempt to fine LinkedIn for its Reference Search feature did not prevail in court because the software feature was not, itself, assembling a consumer report.[224]

II. ANALYSIS

Part I established both the tremendous economic value of predictive talent analytics products and their consequent inevitability, and provided an

diction/ ("While the FTC has rarely used its unfairness authority to enforce against privacy-related injuries, it has used it more regularly to enforce against companies that unreasonably fail to secure individuals' personal data.").

217 FTC v. Wyndham Worldwide Corp., 799 F.3d 236, 240 (3rd Cir. 2015).

218 *See* FTC, 40 YEARS OF EXPERIENCE, *supra* note 7, at 12–13.

219 *Id.*

220 *Id.* at 13 (". . . specifically distinguishing the resale of consumer reports from a company that sells a software system to a company that resells consumer reports.").

221 *Id.*

222 *Id.*

223 *See* Complaint at 3–4, United States v. Spokeo, No. CV12-05001 (C.D. Cal. Jun. 7, 2012).

224 *Sweet,* 2015 WL 1744254, at *9–10.

overview of the diverse types of products on the market.[225] Understanding the types of products on the market proves critical to understanding how the FTC can regulate them under its existing authority and also to identifying which types of products would require additional legislation to regulate. Part I also described the statutory process by which the EEOC and FTC can regulate talent analytics, respectively.[226] The EEOC's approach mirrors the statutory framework of Title VII with respect to disparate treatment and disparate impact cases.[227] Although no specific cases have yet to be brought by the EEOC against talent analytics software under a disparate impact theory, its litigation of employment testing cases provide helpful context for understanding how it might approach predictive algorithms.[228] The FTC, for its part, appears to be using administrative adjudications to define the boundaries for talent analytics software,[229] which is consistent with its generally conservative approach towards rulemaking and the highly involved requirements of the FTC's hybrid-rulemaking process.[230]

This section compares the EEOC's ability to regulate predictive talent analytics against the FTC's and concludes that, although both have a role to play, the FTC's history and the statutory structure of the FCRA position it to better meet the scope and ambiguity involved in regulating predictive talent analytics.[231] Thus, the EEOC should apply its Title VII authority narrowly and the FTC should interpret the FCRA broadly and leverage its Section 5 rulemaking authority to regulate predictive talent analytics.

The analysis proceeds in three phases. First, it considers the hypothetical application of a Title VII claim against a predictive talent analytics product.[232] Second, it recommends that the FTC take a broadened interpretation of the FCRA with respect to talent software and analyzes the viability of this interpretation in light of the statutory language and prior administrative statements.[233] It also analyzes the use of the FTC's Section 5 powers under the FTCA to initiate a formal rulemaking action. Third, it considers and responds to possible objections to the proposed FTC-centric approach to regulating predictive talent analytics.[234]

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225 *See* discussion *supra* Part I.B.1.

226 *See* discussion *supra* Parts I.A and Part I.B.

227 *See* Miaskoff Statement, *supra* note 163, at 12.

228 Predictive algorithms are like employment tests inasmuch as they are looking at data that supposedly predicts success for a particular position or qualifications for a promotion.

229 *See* discussion *supra* Part I.B.1.b.

230 *See* discussion *supra* Part I.C.

231 *See generally* discussion *infra* Parts II.B.2, II.C.2 (describing the scope of the FTC's authority and how its experience with regulating credit reports can be considered analogous in some ways to predictive talent analytics).

232 The hypothetical will reflect an amalgamation of products currently on the market as described in Part I.

233 *See* discussion *infra* Part II.B.2.

234 *See* discussion *infra* Part II.B.3.

A. *Title VII's Difficulties Regulating Predictive Talent Analytics*

The following considers the two potential claims the EEOC could bring under Title VII and concludes that the business necessity defense minimizes the role the EEOC can play in regulating predictive talent analytics.[235] This section sets the stage for the argument that the FTC is better positioned to regulate talent analytics because of its ability and authority to comprehensively address both the data accuracy and quality issues involving predictive talent analytics as well as the possibility that it inadvertently discriminates against protected classes.

1. Disparate Treatment

The EEOC can regulate predictive talent analytics algorithms that explicitly discriminate against protected classes, though they have yet to do so.[236] Using an algorithm to discriminate against a protected class would violate Title VII by facially discriminating against a person on the basis of a protected characteristic vis-à-vis derogatory classification.[237] The irony in the case of big data algorithms, as scholars Solon Barocas and Andrew Selbst note, "is that the use of [a] protected class as an input is usually irrelevant to the outcome in terms of discriminatory effect, at least given a large enough number of input features."[238] Furthermore, litigating a disparate treatment claim with regard to predictive talent analytics can suffer from prohibitive problems of proof.[239] Thus, Title VII analysis of predictive talent analytics would fall predominantly under the disparate impact test.

2. Disparate Impact

In the hypothetical described at the beginning of this Comment, you chose not to pursue litigation because of its high cost. The following will analyze what would have likely occurred should you have chosen to pursue your claim.

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235 *See* discussion *infra* Part II.C.

236 *See* discussion *supra* Part I.B.1.a.

237 *See id. See also* Barocas & Selbst, *supra* note 8, at 695 ("Because classification itself is a legal harm, irrespective of the effect, the same should be true of using protected class as an input to a system for which the entire purpose is to build a classificatory model.") (citations omitted).

238 Barocas & Selbst, *supra* note 8, at 695.

239 *See* GORDON, *supra* note 68, at 27. *See also* discussion *supra* Part I.A.3. It is worth noting that problems of proof are not unique to disparate treatment cases—they also challenge disparate impact cases.

The first difficulty is proving a prima facie case of discrimination.[240] Because of the complexities of big data models, retaining the expertise required to properly litigate the case could prove difficult.[241] Even with the appropriate experts, you must prove that the *particular employment practice* of using predictive talent analytics resulted in a statistically validated disparate impact on your protected minority.[242] Unlike historical cases involving employment tests,[243] which were fixed methods for determining employability, this may prove impossible, because the results and methods of a predictive analytics formula constantly change as it learns from an ever-growing amount of data.[244] Assuming a prima facie case can be established under the EEOC's Eighty Percent rule and can causally connect the disparate impact to the predictive analytics algorithms, the burden will shift to the business to show a business necessity for the use of talent analytics software.[245]

Depending on the circuit, the business necessity defense will be applied with slightly varied understandings of what constitutes a business necessity.[246] In any case, it is not enough for a business to argue that the total outcome of its hiring process, of which predictive talent analytics was a part, was non-discriminatory.[247] Rather, the employer would be required to show that the predictive analytics application it uses is itself a business necessity; if you had narrowed the discriminatory aspects to a particular line of code, it might need to justify the code.[248] All of the circuits apply some form of a job-relatedness standard.[249] Assuming your employer's big data model was

240 Courts have been hesitant to provide a low bar to plaintiffs in disparate impact cases. *See, e.g.*, Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmty. Project, Inc., 135 S. Ct. 2507, 2524 (2015) ("If the specter of disparate-impact litigation causes private developers to no longer construct or renovate housing units for low-income individuals, then the FHA would have undermined its own purpose as well as the free-market system.").

241 *See Next Generation Computing Joint Hearing*, *supra* note 36, at 8 (predicting a shortfall in the number of professionals with technical depth in data analytics); *see also* GORDON, *supra* note 68, at 27.

242 42 U.S.C. § 2000e-2(a)(1) (2012) ("It shall be an unlawful *employment practice* . . . to discriminate against any individual . . . because of such individual's race, color, religion, sex, or national origin . . . .") (emphasis added).

243 *See* discussion *supra* Part I.B.1.b (explaining several examples of disparate impact litigation with respect to testing cases).

244 *See* GORDON, *supra* note 68, at 21–26.

245 *See* discussion *supra* Part I.B.1.b (describing the burden shifting scheme for disparate impact cases).

246 Barocas & Selbst, *supra* note 8, at 702–06 (providing a review of several circuits application of business necessity and job-relatedness).

247 *See* Connecticut v. Teal, 457 U.S. 440, 452 (1982).

248 *See* discussion *supra* Part I.B.1.b (discussing particular aspects of tests that violated Title VII); *see also* El v. Se. Pa. Transp. Auth., 479 F.3d 232, 239–41 (3d Cir. 2007) (providing examples of various testing cases where particular components of tests were struck down as violations of Title VII).

249 The Third District briefly flirted with a strict business necessity standard but then reverted to a job-relatedness standard. *See* Barocas & Selbst, *supra* note 8, at 705–06 (providing a helpful review of the varying standards applied by the federal circuit courts).

properly designed, it is, by definition, certain to demonstrate that the combination of the underlying points statistically correlate to job performance.[250] Once the employer has demonstrated its correlation, an employee could attempt to demonstrate a less discriminatory alternative but, again, problems of proof are inevitable.[251]

In sum, Title VII's primary contribution to regulating predictive talent analytics lies in its prohibition of using algorithmic formulas to explicitly discriminate against a protected class. A disparate impact claim, in the case of talent analytics, will be difficult to prove and will likely fail as a ground for overcoming the business necessity exception. Nevertheless, the FTC via the FCRA can serve as a helpful regulating body upon predictive talent analytics, as analyzed in the following section.

B. *Using the FCRA and FTCA to Regulate Predictive Talent Analytics Applications*

Predictive talent analytics software can be divided into three scenarios for analysis, each of which receives a different degree of coverage under the FCRA: (1) software that mines big data from diverse external sources to generate reports for talent acquisition teams;[252] (2) software that enables the end user to analyze data that is internal to the end user's business and data that is external to the company in order to automate decision-making;[253] (3) and software that enables the end user to analyze data that is strictly internal business data in order to automate decision-making.[254] The following analyzes each scenario under the two relevant aspects of the FCRA: (a) its definition of CRA; and (b) its definition of consumer report (including explicit statutory exclusions).

1. Scenario One: Diverse Data Sources Generating Reports for Third Parties

Scenario One, in which a program analyzes diverse external data sources and thereafter generates reports for third parties, most clearly meets the parameters of FTC regulation under the FCRA. First, it meets the definition of a CRA because it regularly collects "information on consumers" with

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250 HALO BI, *supra* note 1 (defining descriptive, predictive, and prescriptive analytics).

251 *See* GORDON, *supra* note 68, at 27; *see also* discussion *supra* Part I.A.3.

252 *See, e.g.*, Complaint at 4, United States v. Spokeo, No. CV12-05001 (C.D. Cal. Jun. 7, 2012).

253 *See, e.g.*, *Kiran Analytics*, *supra* note 73.

254 *See, e.g.*, Ring, *supra* note 74 (describing Cornerstone OnDemand). The points above are listed in descending order of the ease of regulation under the FCRA, with (1) most clearly falling within the scope of the FCRA, (2) arguably fitting within the scope of the FCRA, and (3) probably not fitting within the FCRA in its current form.

the purpose of "furnishing . . . reports to third parties."[255] Second, its output generates a report that is delivered to a third party, presumably for employment purposes.[256] Third, its operation does not fall under any definitional exclusions of a consumer report within the FCRA.[257]

A case involving the web-based talent management software provider Spokeo most closely resembles this scenario.[258] The FTC brought an administrative action against Spokeo for several violations under the FCRA.[259] Spokeo's web product re-packaged publically available information for recruiters and employers.[260] The product employed deep web crawlers to aggregate profiles on individuals and sold the aggregated candidates' profiles to prospective employers.[261] Spokeo developed Application Program Interfaces that integrated with its customers systems so that its data could be used to inform hiring decisions.[262] The FTC alleged that Spokeo was a CRA that furnished consumer reports, as defined under the FCRA,[263] because its product regularly assembled information on consumers into reports and distributed them to third parties.[264] Further, the FTC pointed to the FCRA's applicability to Spokeo's reports because they were expected to be used for employment purposes.[265]

The FTC alleged that Spokeo's product did not take reasonable steps to ensure the aggregated consumer information was used for permissible purposes, which would have included a reasonable effort to verify the users and uses of Spokeo reports.[266] Additionally, Spokeo did not follow reasonable procedures to ensure the accuracy of the data its system was collecting about individuals. The FTC alleged that the absence of any safeguards to ensure data accuracy constituted "unfair or deceptive acts" pursuant to section 621(a)(1) of the FCRA.[267] Also, Spokeo did not provide user notices regarding use of consumer reports to its customers as required under 15 U.S.C. §

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255 15 U.S.C. § 1681a(f) (2012).

256 *Id.*

257 *Id.*

258 *See generally*, Robins v. Spokeo, Inc., 742 F.3d 409 (9th Cir. 2014); Complaint, United States v. Spokeo, No. CV12-05001 (C.D. Cal. Jun. 7, 2012).

259 Complaint at 7–9, United States v. Spokeo, No. CV12-05001 (C.D. Cal. Jun. 7, 2012).

260 FTC Press Release, *supra* note 75; Angela Preston, *A Growing Question: Just How Effective Is Big Data In Hiring?*, ERE MEDIA (March 2015), http://www.eremedia.com/tlnt/a-growing-question-just-how-effective-is-big-data-in-hiring/.

261 DAVAD TARAS, DIGITAL MOSAIC: MEDIA, POWER, AND IDENTITY IN CANADA 24 (2015) (describing Spokeo as a site which "scour[s] the Internet using deep web crawlers for any available information on their targets . . .").

262 Complaint at 4, United States v. Spokeo, No. CV12-05001 (C.D. Cal. Jun. 7, 2012). API's are intermediary software languages that allow two or more systems to communicate with each other.

263 *Id.* at 1–2.

264 *Id.* at 5–6.

265 *Id.*

266 *Id.* at 7.

267 Complaint at 8, United States v. Spokeo, No. CV12-05001 (C.D. Cal. Jun. 7, 2012).

1681e(d).[268] Spokeo settled with the FTC, paying an $800,000 fine and agreeing to be monitored by the FTC for the next twenty years to ensure compliance with the alleged violations of the FCRA.[269]

Thus, talent analytics products, such as Spokeo, that use external data sources to serve a reporting function to third parties reasonably fall under the definition of a CRA. If the software products output is used for an employment purpose, then it would fall under the FCRA.

2. Scenario Two: Software Enabled Analysis of Diverse Data Sources by End Users

Based on how the FTC currently interprets a consumer report under the FCRA, it would likely not find Scenario Two to fall under the FCRA because the end user, not the software provider, uses the software to compare both internal and external data sources to inform employment decisions.[270] Although the FTC currently considers companies that merge data sources and resell them to be CRAs, it does not deem software providers that enable the merging of data sources with their products to be CRAs.[271] Thus, Spokeo's product was considered to create merge and purge reports because it collected information from third parties, generated reports, and *then* sold them to third parties.[272] Presumably, a product that enables end users to perform the task of collecting and assembling data about a potential employee themselves would not be considered a consumer report, even though the output substantially resembles a consumer report, solely because of who leverages the software.

This scenario creates a loophole in the FTC's understanding of the FCRA as applied to talent analytics software. This loophole is important, because talent analytics software increasingly focuses on providing talent management teams end-to-end solutions that integrate multiple data sources into self-service dashboards.[273] This reflects both a general trend toward automa-

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268 *Id.* at 9.

269 *See* FTC Press Release*, supra* note 75.

270 Although this does not fall under any of the explicit exclusions in section 603(d)(2), which defines exclusions for consumer reports, it appears to fall outside of the FTC's current understanding of the definition of a CRA. 15 U.S.C § 1681(a) (2012) (stating that to exclude a report from the definition of consumer report it must contain information "*solely* as to transactions or experiences between the consumer and the person making the report") (emphasis added); *see* FTC, 40 YEARS OF EXPERIENCE, *supra* note 7, at 23–24.

271 *Id.* at 12–13.

272 Complaint at 4–6, United States v. Spokeo, No. CV12-05001 (C.D. Cal. Jun. 7, 2012).

273 *See* discussion *supra* Part I.A.1 (explaining the evolution of talent software to meet the particular needs of the talent management space).

tion as well as the particular dearth of technical talent within talent management organizations discussed in Part I.[274] Thus, the software products themselves begin to fill the traditional function of the data broker and, by removing the middle-man, potentially escape regulation.

The FTC's interpretation can, and should, evolve to meet emerging talent analytics technology. Section 629, entitled "Corporate and technological circumvention prohibited," provides a potential means to do so.[275] This section empowers the CFPB[276] to "prescribe regulations" that "prevent a [CRA] from circumventing or evading treatment as a CRA" within the purpose of the FCRA.[277] Although the particular examples mentioned in the statute relate to corporate restructuring and organizations maintaining and merging records similarly to CRAs, the CFPB's rulemaking power under Section 629 does not limit it to those particular examples.[278]

The CFPB should use its Section 629 power to prescribe regulations to include software providers whose products function similarly to data brokers within its understanding of CRAs, subject to all of the requirements therein. Thus, rather than limit CRAs to persons who "[assemble] or [evaluate] . . . information . . . for the purposes of furnishing consumer reports to third parties," it would include software providers whose products enable the third parties to assemble the information themselves.[279] In the employment context, such a change means the software provider must receive certification from the employer that is using the product consistent with the requirements of the FCRA—namely, that the employer disclose the generation of a report about a particular employee or applicant.[280] In cases where an adverse employment action is taken, the employer must provide the employee with a copy of the report as well as their consumer rights.[281] This report provides employees sufficient access to their data and the power to correct inaccuracies, as well as seek legal recourse for civil remedies when appropriate.[282]

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274 *See id.* (explaining talent management's technical talent gap).

275 15 U.S.C. § 1681x (2012).

276 This paper recognizes that there is a difference between the FTC's role and the CFPB's role under the FCRA after new regulations released in 2011 as part of the Dodd-Frank Act. These new regulations, however, do not impact this analysis.

277 15 U.S.C. § 1681x (2012).

278 *See id.*

279 15 U.S.C. § 1681a(f) (2012).

280 15 U.S.C. § 1681b (2012).

281 *Id.*

282 *See id.*

3. Scenario Three: Software Enabled Analysis of Internal Data by End Users

Scenario Three certainly falls outside of the definition of a consumer report based on the business transaction exclusion in the FCRA.[283] Even if the definition of CRA as proposed above were expanded to include software products, the FCRA excludes any "report containing information solely as to transactions or experiences between the consumer and the person making the report," as well as communication about the report within common corporate control.[284] Because Scenario Three aggregates only data generated by employees within the context of work performed for their employers, it does not fall under the FCRA. Given the existing statutory language, a talent analytics product that solely enabled talent management teams to mine internal corporate data for predictive results would not be considered a consumer report. Nevertheless, the FTC could still regulate this third category of talent analytics products without any additional legislation vis-à-vis its authority under the FTCA.

The FTC could use its Section 5 authority under the FTCA to regulate predictive talent analytics practices directly.[285] Section 5 bans "unfair or deceptive acts or practices" affecting commerce and permits the FTC to declare a practice unfair if it (1) "causes substantial injury to consumers," (2) "is not reasonably avoidable by consumers," and (3) is "not outweighed by countervailing benefits to consumers or to competition."[286] Under this framework, the FTC could potentially implement regulatory oversight of predictive talent analytics. FTC rulemaking might: (a) require quality standards for predictive data models used in the employment context, including checks to ensure they do not unintentionally exclude protected classes; (b) ensure businesses employ processes to ensure data quality and accuracy when it is being used by a predictive talent algorithm; and (c) require both notice and opportunities to correct data to employees affected by predictive talent analytics at their companies.

Were the FTC to adopt this approach, its hybrid rulemaking authority would ensure extensive industry feedback and involvement in the construction of the final requirements.[287] Indeed, each of the three elements required to declare a practice unfair under the FTCA Section 5 powers are present in the case of predictive talent analytics. First, poor data models and inaccurate data can cost employees their livelihoods, satisfying the first element.[288] The

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283 *See* 15 U.S.C. § 1681a(d)(2) (2012) (defining exclusions to the definition of a consumer report).

284 15 U.S.C. § 1681a(d)(2)(A) (2012).

285 15 U.S.C. § 45 (2012).

286 15 U.S.C. § 45(m)–(n) (2012).

287 *See generally* OVERVIEW OF FED. AGENCY RULEMAKING, *supra* note 210, at 9–13.

288 *See* discussion *supra* Parts I.A.2–3 (describing widespread corporate data quality issues, data model design challenges, as well as the discriminatory potential of big data predictions).

cost to consumers can be analogized to consumers who are the victims of inaccurate data in their credit scores.[289] Second, injuries produced by talent analytics software cannot be reasonably avoided by employees or applicants, because they have no visibility into the data or processes determining a particular employment action.[290] In fact, they may never become aware of the fact that a predictive talent analytics product adversely effected them at all.

The third element proves to be the most challenging to establish because of the substantial economic benefits of predictive talent analytics; nevertheless, prudent regulatory steps can be justified. Talent analytics constitutes a $10 billion emerging market undergoing rapid innovation.[291] It promises to generate much needed efficiencies within the talent management space and create value across corporate enterprises by better identifying and utilizing talent pools.[292] The FTC, then, must balance the needs of the consumer—the employees and applicants—against the needs of business, and show sensitivity to the environment that is required to foster innovation in the field of talent analytics.[293] This balance does not need to be an "either/or" scenario. Prudent processes to validate the effectiveness of data models, the accuracy and quality of data, the protection of protected classes, and transparency with employees can generate increased efficiency for businesses and consumers.[294] Bad data models create bad results for businesses and poor data quality already constitutes a large financial drain on business.[295] Furthermore, data suggests that diversity of all kinds can positively impact a business's bottom-line, and transparency can improve culture leading to superior business performance.[296]

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289 *See* discussion *infra* Part II.C.1 (analogizing predictive talent analytics to the FICO score—the first popularized predictive algorithm—and suggesting that the FTC's experience regulating credit scores suits it to provide the type of balancing of interests necessary to regulate predictive talent analytics.

290 *See* discussion *supra* Parts I.C.2–3 (defining the limits of software platforms in the employment context under the FCRA).

291 Bersin, *supra* note 38.

292 *See* discussion *supra* Part I.A.1 (describing the current economic value and future economic potential of predictive talent analytics).

293 *See* Hirsch, *supra* note 216 (describing the third balancing prong of the FTC's Section 5 authority as "a vehicle through which the FTC can undertake this crucial balancing" within the big data context).

294 *See* discussion *supra* Part I.A.2 (highlighting the cost of poor data, and low employee engagement).

295 *Id.* This point follows logically from the purpose of big data analytics—to create business value by generating efficiencies and enabling smarter decisions. If the model is flawed and does not create correct outputs, then the result will likely be decreased efficiency and poorer business decisions.

296 Michele E. A. Jayne & Robert L. Dipboye, *Leveraging Diversity to Improve Business Performance: Research Findings and Recommendations for Organizations*, 43 HUMAN RES. MGMT. 409, 422 (2004) (Dispelling the myth that diversity alone empirically correlates to improved business outcomes, but demonstrating that if it is property done, ". . . achieving a diverse workforce and effectively managing this workforce can yield huge benefits"); *see also 7 Vital Trends Disrupting Today's Workplace*, TINYPULSE (2013), https://www.tinypulse.com/resources/employee-engagement-survey-2013 (conducting a study of over 300 global organizations and concluding that "[m]anagement transparency is the top

C. *Possible Objections*

Although there are several possible objections to an FTC-centric approach to regulating the talent analytics industry, using the FTC would provide the most flexible and least burdensome oversight of the talent analytics industry while protecting employees. The following considers several potential objections.

1. Legislative Solution

In light of the risks associated with big data analytics and current law's inability to effectively address them,[297] some academics recommend that lawmakers revisit the laws regulating big data entirely.[298] Certainly, enacting new legislation that implements a comprehensive regulatory regime for big data reflects an appropriate appreciation for the degree to which big data is transforming the modern economy and could, presumably, include protections with respect to predictive talent analytics.[299]

Opting for comprehensive reform could provide greater protections than using current statutory authority via agency rulemaking to adapt the statutes to the case of predictive talent analytics, as this Comment suggests is appropriate. Although comprehensive legislation may be appropriate in the future, there are two reasons to wait and let the FTC assume a leadership role in talent analytics regulation under existing statutes.

First, big data analytics is an emerging market.[300] Although talent analytics alone already represents a multibillion dollar market, the market continues to grow.[301] Establishing comprehensive rules *ex ante* for unknown future technological innovations risks allowing well-intentioned regulatory missteps and creating a chilling effect on innovation.[302] By leveraging the FTC's authority under the FCRA and FTCA to provide modest oversight of

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factor when determining employee happiness . . . [with a] correlation coefficient of .93 with employee happiness.").

297 *See* discussion *supra* Parts I.A.2-3.

298 *See, e.g.*, Burdon & Harpur, *supra* note 2, at 712 (concluding that big data requires a "paradigm shift . . . for how we approach the inequalities that could arise through talent analytics" to develop a new framework to think about big data); *see also* Barocas & Selbst, *supra* note 8, at 725–28 (suggesting the need for a new approach in general and identifying non-legal options to ameliorate the challenges of predictive analytics).

299 Big data implicates privacy, discrimination, due process, and affects many fields. *See, e.g.*, Nicholas P. Terry, *Protecting Patient Privacy in the Age of Big Data*, 81 UMKC L. REV. 385, 388–97 (2012) (describing big data and healthcare data pools).

300 GOOD ET AL., *supra* note 28, at 2, 5.

301 Bersin, *supra* note 38.

302 Comprehensive legislation of a complex and evolving field inherently comes with risks of unintended consequences.

predictive analytics in the employment context, industries would be able to provide substantial feedback to inform the final rules, and the FTC would retain the flexibility to adapt the rules to an evolving technological landscape.[303] Specifically, the FTC's ability to use administrative actions to set precedent and set the stage for formal rulemaking gives it superior flexibility to congressional action.[304]

Second, the FTC is uniquely suited to regulate predictive talent analytics, because of its track record regulating consumer credit scores, such as the FICO score,[305] which could be considered the first popular predictive algorithm.[306] Like predictive talent analytics, which predict a variety of employee behaviors, the success of the FICO score can be credited, in no small part, to its general success at predicting risk of default on loans.[307]

Additionally, the criticisms of predictive talent analytics also mirror many of the criticisms leveled against credit scores. Critics argue that credit scores create an algorithmic disparate impact through secondary effects;[308] they point to widespread data quality issues regarding credit scores and how those issues implicate core questions of fairness.[309] For example, the ranking member of the House Committee on Financial Services said, "The linchpin of the system that goes into determining the credit score has to be complete. It has to be accurate. Otherwise, the outcome is going to be misleading, and frankly, I think ultimately that hurts the consumer."[310] In a very real sense, these types of concerns birthed the FCRA and created a framework by which

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303 *See* discussion *supra* Part II.B.2 (describing the hybrid rulemaking process).

304 *Id.*

305 FICO's scoring regime is evolving and several competitive products are on the market. Ioannis Hatzilygeroudis & Jim Prentzas, *Fuzzy and Neuro-Symbolic Approaches in Personal Credit Scoring: Assessment of Bank Loan Applicants*, *in* INNOVATIONS IN INTELLIGENT MACHINES-4: RECENT ADVANCES IN KNOWLEDGE ENGINEERING 319, 320–21 (Colette Faucher & Lakhmi C. Jain, eds., 2014) (describing a variety of credit scoring methods used by various institutions); Frederic Huynh, *Adapting Credit Scores to Evolving Consumer Behavior and Data*, 46 SUFFOLK U. L. REV. 829, 830 (2013);.

306 Huynh, *supra* note 305, at 831–32 (describing the predictive elements of the FICO score).

307 Anthony Pennington-Cross & Joseph Nichols, *Credit History and the FHA-Conventional Choice*, 28 REAL ESTATE ECON. 307, 309–13, 318 (2000) (validating the score's general predictive value for mortgage repayments); Ellen Y. Yan, *Refining Credit-Review Policy for Small Business*, 15 COM. LENDING REV. 39, 39-40 (2000) (finding ". . . that FICO scores are a good proxy for default risk . . . [and the] default rate is generally lower when the FICO score is higher.").

308 *See, e.g.*, Cassandra Jones Havard, *"On the Take": The Black Box of Credit Scoring and Mortgage Discrimination*, 20 B.U. PUB. INT. L.J. 241, 244–45 (2010) (describing the "second generation" discrimination of credit scores).

309 *Id.* at 269.

310 *Keeping Score on Credit Scores: An Overview of Credit Scores, Credit Reports, and Their Impact on Consumers: Hearing Before the H. Subcomm. on Fin. Inst. & Consumer Credit*, 111th Cong. 5 (March 24, 2010) (statement of Rep. Hensarling).

consumers had rights and a means of transparency.[311] Given the analogous functionality of, and mirroring criticisms against, credit scores and talent analytics, the FTC is most suited to provide oversight of predictive talent analytics.

2. An FTC-Centric Approach Insufficiently Protects Against Discrimination

In light of criticisms of the FTC and FCRA regarding ameliorating the discriminatory effects of credit scores, some might question whether an FTC-centric approach towards predictive talent analytics can adequately address the discriminatory potential of talent analytics. This concern has merit, given concerns about the potentially discriminatory impact of credit scoring practices.[312] Nevertheless, there are two reasons to start with an FTC-centric approach even if it does not fully address discriminatory outcomes.

The first is that the disparate impact framework does not provide a means of balancing the needs of business with discrimination in a world of talent analytics employing big data.[313] Forcing this framework on predictive talent analytics will either be entirely ineffective—because of the business necessity exception—or suppress innovation because it will be difficult to predict the outcomes of a talent analytics solution that employs machine learning.[314] Fully addressing the discriminatory potential of predictive talent analytics must be a recursive process over the next many years, because the talent analytics technology will itself evolve and with it will come a renewed discussion concerning what is and is not discrimination.[315]

Second, implementing an FTC-centric approach immediately may promote just the dialogue and transparency needed to advance the necessary dialogue with respect to discrimination. Currently, the FCRA provides a framework requiring disclosures and opportunities to correct data discrepancies in a person's credit report.[316] Providing a similar approach to predictive analytics in the employment context may be able to generate just that kind of debate with respect to the discriminatory effects of predictive talent analytics.

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311 *See* 15 U.S.C. § 1681(a) (2012) ("Inaccurate credit reports directly impair the efficiency of the banking system, and unfair credit reporting methods undermine the public confidence which is essential to the continued functioning of the banking system.").

312 *See*, Havard*, supra* note 308, at 287.

313 *See* discussion *supra* Part II.A.2 (discussing the limitations of Title VII at regulating predictive talent analytics).

314 *Id.*

315 *See* Bersin, *supra* note 38 (describing the emerging market of talent analytics).

316 *See* FTC, 40 YEARS OF EXPERIENCE, *supra* note 7, at 64, 70, 74.

CONCLUSION

Predictive talent analytics is here to stay. The question is not whether it will transform business, but rather how employment law will handle it. Although predictive talent analytics promises tremendous economic opportunities for employers, it comes at a risk to both employees and job seekers. Poor data quality, improperly implemented models, and a lack of meaningful mechanisms to provide employees transparency implicate core questions of fairness. Furthermore, even the best-designed data models risk producing discriminatory impacts on protected classes of people by assigning non-blatant proxies. Machine learning creates a further complication where even the designer of the data model no longer possesses full knowledge of why or how the machine evolved its parameters in response to the data it was receiving.

Although at first blush Title VII's disparate impact theory appears to be a promising starting point, its burden-shifting scheme makes regulation of predictive talent analytics impractical. By definition, a properly implemented predictive talent analytics system will provide statistically valid workforce predictions. The more promising means to approach predictive talent analytics is through the FTC. The FTC's hybrid rulemaking structure can create adequate space for business inputs to thoughtfully address the risks associated with emerging talent analytics technology. Although this approach does not fully tackle the problem of discriminatory effects, it guarantees a level of quality for data and predictive models as well as a more transparent environment where core questions of discrimination can be explored as predictive talent analytics grows as a field. The FCRA already contains a framework to provide employees disclosure and an opportunity to remedy data discrepancies. In fact, this framework emerged from challenges relating to the first widely used predictive algorithm—credit scores.

Predictive analytics promise to play an increasing rule in corporate talent management; its speed and accuracy enable businesses to make smarter decisions at lower costs. However, the potential consequences of this technology to individual employees and protected classes warrant government oversight. Should the FTC take a lead role in providing such oversight, companies will be able to retain the benefits of this emerging technology and employees will not have to bear the full cost.