

Be Used to Predict Arbitration Claims and Outcomes

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ARBITRAL ANALYTICS: HOW MONEYBALL BASED LITIGATION/JUDICIAL ANALYTICS CAN BE USED TO PREDICT ARBITRATION CLAIMS AND OUTCOMES

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"In God we trust. All others must bring data."2

I. INTRODUCTION

Attorneys are typically hired when a dispute arises or when a contract is drafted. This "common law" method of attorney involvement represents an archaic and outdated form of legal representation and advocacy.³ Instead, imagine a world where attorneys become involved with the business decision process well before the parties are even introduced to each other.

For example, if party A was looking to find a product vendor or manufacturer, it would start with a list of potential party Bs who could meet its vendor requirements for the product, but there would be extra steps in-between. Hypothetically, party A's attorney would start by reviewing the historical litigation and arbitrations undertaken by the potential party B.

Thereafter, the attorney would deduce the potential outside counsel party B would pick if a dispute arises, and from this list, determine the potential claims which might arise between

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² Professor William Edwards Deming; OXFORD ESSENTIAL QUOTATIONS, OXFORD UNIV. PRESS 1900–03 (Susan Ratcliffe 6th ed., 2018).

³ Robert Weber, *Will the "Legal Singularity" Hollow Out Law's Normative Core?*, 27 MICH. TECH. L. REV. 97, 99–164 (2020); Michael Guihot, *New Technology, the Death of the Biglaw Monopoly and the Evolution of the Computer Professional*, 20 N.C. J.L. & TECH. 405, 408–14 (2019).

parties A and B. From here, the attorney would enlist outside counsel to determine which judges, arbitrators, and mediators would be favorable to party A at the expense of party B—essentially tilting the game in the favor of Party A.

Presently, the most advanced international and domestic attorneys do not use technology when addressing issues raised by governments, international disputes, or U.S. domestic disputes.⁴ In fact, these attorneys usually search online databases such as Lexis Nexis, Westlaw, and Bloomberg Law solely for legal precedent and regulations.⁵ However, these services and many more offer a vast pool of data that can be used for analytics beyond the average attorney's imagination or comprehension. In fact, there are several analytics specific companies which can take an attorney's research skills light years ahead of where they are now.⁶ Furthermore, this vast wealth of data launches all new opportunities and ethical chasms that have yet to be discovered or debated.⁷

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⁴ Ashley Deeks, *High-Tech International Law*, 88 GEO. WASH. L. REV. 574, 576 (2020) (citing Wolfgang Alschner, Joost Pauwelyn, & Sergio Puig, *The Data-Driven Future of International Economic Law*, 20 J. INT'L ECON. L. 217, 218 (2017)).

⁵ Litigation Analytics, LEXIS NEXIS [hereinafter LEXIS], https://www.lexisnexis.com/en-us/home.page (last visited Nov. 6, 2020); Litigation Analytics, WESTLAW EDGE [hereinafter WESTLAW], https://legal.thomsonreuters.com/en/products/westlaw (last visited Nov. 6, 2020); Litigation Analytics, BLOOMBERG L. [hereinafter BLOOMBERG], www.bloomberglaw.com%252Fstart%26v%3D0.1018.3 (last visited Nov. 6, 2020); Jan Bissett & Margi Heinen, Beyond Court Decisions—Dockets, Documents, and Analytics, 46 Colo. LAW. 59, 59–61 (2017) (discussing analytics in Lexis Nexis, Westlaw, and Bloomberg Law subscription services).

⁶ Several U.S. based litigation analytics companies exist, but two notable start-ups include: Premonition.ai and Gavelytics.com. PREMONITION.AI, https://premonition.ai/ (last visited July 1, 2020); GAVELYTICS, https://www.gavelytics.com/ (last visited July 1, 2020). They provide vast quantities of data for courts, judges, attorneys, arbitrators, and parties to disputes.

⁷ Pamela Stewart & Anita Stuhmcke, *Judicial Analytics and Australian Courts: A Call for National Ethical Guidelines*, 45 ALT. L.J. 82, 82–87 (2020); Andrew Cohen, *California State Bar Opinion on Litigation Funding Could Have Sway*, BL LEGAL ETHICS NEWS (Oct. 26, 2020, 1:00 A.M.), https://www.bloomberglaw.com/document/X77I715O000000?bna_news_filter=us-law-week&jcsearch=BNA%252000001753315dac2a3753b177f510001#jcite (discussing three issues California attorneys must consider before accepting litigation financing in a California jurisdiction: (1) a

A. THE SIGNIFICANCE OF ANALYTICS

Turning to the significance of analytics and databases, any party could use them to determine the costs, risks, and ultimate outcome to their case. Indeed, the current process attorneys utilize for conflict checking, case analysis, litigation timelines, forum shopping, research, and evaluating the opposing parties is obsolete. Thus, no one should even contemplate litigation, arbitration, mediation, or negotiation without first consulting an analytics database for potential issues they might be drawn into if a contract is signed, or a claim arises during performance. Furthermore, litigation analytics can be used for a myriad of purposes when a claim arises such as due diligence, win-to-loss ratios, judicial history, an attorney's cases before a particular judge, legal writing styles, legal precedent preferred by certain judges, dispositive motion ratios, discovery grants, and many more undiscovered analytics.

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lawyer's duty of loyalty to the client, (2) a client's informed consent before sharing confidential information with a litigation financing third party, and (3) the legality of litigation financing without violating champerty rules.).

⁸ Dru Stevenson & Nicholas J. Wagoner, *Bargaining in the Shadow of Big Data*, 67 FLA. L. REV. 1337, 1364 (2015).

⁹ See William J. Connell, Artificial Intelligence in the Legal Profession—What You Might Want to Know, 66 R.I. BAR J. 5, 5–44 (2018) (citing Steve Lohr, A.I. Is Doing Legal Work. But It Won't Replace Lawyers, Yet., N.Y. TIMES (Mar. 19, 2017), https://www.nytimes.com/2017/03/19/technology/lawyers-artificial-intelligence.html) (finding only 4% of a lawyer's time at large law firms is used for document review)); Daniel L. Chen, Judicial Analytics and the Great Transformation of American Law, 27 A.I. & L. 15, 17 (2018) ("American law was characterized by a shift to a consequentialist mode of reasoning about the law and a focus on efficiency, then judicial analytics might be the next step in this great transformation, to move from theorizing about the consequences of law to measuring the consequences of law and a focus on fairness."); Daniel Ben-Ari, Yael Frish, Adam Lazovski, Uriel Eldan, & Dov Greenbaum, Artificial Intelligence in the Practice of Law: An Analysis and Proof of Concept Experiment, 23 RICH. J.L. & TECH. 3, 35–39 (2017) ("We can predict that in the long run, AI technologies using machine learning and deep learning techniques may replace lawyers, arbitrators, mediators, and even judges."); Gizem Kasap, Can Artificial Intelligence ("AI") Replace Human Arbitrators? Technological Concerns and Legal Implications, 2021 J. DISP. RESOL. 209, 237–40 (2021).

¹⁰ Stewart & Stuhmcke, *supra* note 7, at 83 (citing Toby Unwin, *Legal Analytics Firm, Premonition, Publishes Statistical Ranking of Australia's Top Law Firms and Barristers*, PREMONITION NEWS (Sept. 6, 2017), https://premonition.ai/legal-analytics-firm-premoniton-publishes-statistical-ranking-australias-top-

In addition to the numerous analytics available to each case, a party could apply artificial intelligence (AI), machine learning (ML); support vector machines (SVM); time series (TS);natural language processing (NLP); and neural networks (NN) to these pools of data which promise to revolutionize the legal, judicial, and arbitral professions. Given the overwhelming amount of research into written language processing via AI (a blanket term for the aforementioned list), it is no surprise many in the computer science field and a select few in the legal industry are predicting the rise of case outcome prediction by AI within the next decade or

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law-firms-barristers/ (finding a client's choice of attorney and law firm increased the chances of winning by 30.7%)); Tom Martin, *The Future of AI in Legal Tech: What Will the Law Allow?*, A.B.A. (Dec. 13, 2019), https://www.lawpracticetoday.org/article/the-future-of-ai-in-legaltech-what-will-the-law-allow/?utm%20source=Dec19&utm%20medium=%20email&utm%20campaign=Dec19LPTemail; Agnieszka McPeak, *Disruptive Technology and the Ethical Lawyer*, 50 U. Tol. L. Rev. 457, 464 (2019).

¹¹ Chen, supra note 9, at 26–32; Thomas Vacek, Ronald Teo, Dezhao Song, Conner Cowling, Frank Schilder, & Timothy Nugent, Litigation Analytics: Case Outcomes Extracted from US Federal Court Dockets, PROC. NAT. LEGAL LANGUAGE PROCESSING WORKSHOP 2019 45, 47–50 (2019) [hereinafter Vacek Case Outcome] (SVM application to PACER data); Stacia L. Haynie, A Time Series Analysis of the Functional Performance of the United States Supreme Court, 1–258 (1990) (TS); Thomas Vacek, Dezhao Song, Hugo Molina-Salgado, Ronald Teo, Conner Cowling, & Frank Schilder, Litigation Analytics: Extracting and Querying Motions and Orders from US Federal Courts, PROCS. NORTH AM. CH. ASS'N COMPUTATIONAL LINGS,-HUM, LANG, TECHS, 2019: DEMONSTRATIONS, 116, 118, 120 (2019) [hereinafter Vacek Motions and Orders] (SVM/NLP/various ML); Pontus Stenetorp, Samp Pyysalo, Goran Topic, Tomoko Ohta, Sophia Ananiadou, & Jun'ichi Tsujii, BRAT: A Web-based Tool for NLP-Assisted Text Annotation, 13TH CONF. ASS'N COMPUTATIONAL LINGS, 102, 102–06 (2012) (NLP/BRAT/STAV); Priya Dwivedi, NLP: Extracting the Main Topics from Your Dataset Using LDA in Minutes, Towards Data Sci. (Aug. 22, 2018), https://towardsdatascience.com/nlp-extracting-the-maintopics-from-your-dataset-using-lda-in-minutes-21486f5aa925 (discussing NLP and Latent Dirichlet Allocation (LDA)); see Chad M. Oldfather, Joseph P. Bockhorst, & Brian P. Dimmer, Triangulating Judicial Responsiveness: Automated Content Analysis, Judicial Opinions, and the Methodology of Legal Scholarships, 64 FLA. L. REV. 1189, 1240 (2012) (discussing SVM and multiple regression modeling (MRM)); S.T.L.A. Mulders, Which Type of Lawyer Wins Most Cases? A Quantitative Study of Dutch Court Cases, TILBURG UNIV. 5, 23–37 (2016) (using crawler software to analyze Dutch civil law cases for litigation analytics).

even sooner.¹² Furthermore, there is rising evidence of AI replacing attorneys, paralegals, and legal secretaries for many tasks throughout the legal industry.¹³

Therefore, since the rise of AI based litigation analytics is at hand, it behooves all attorneys to not only take this paper seriously but to re-imagine their practice to include analytics throughout their workflow, in the courtroom, or arbitration hearing.

B. PAPER SYNOPSIS

AI based litigation, judicial, and arbitral analytics is a complex subject with hundreds or even thousands of moving parts, so this paper will be split into eight parts: (II) a detailed background on analytics and the promise analytics has to revolutionize claims; (III) the numerous issues surrounding analytics such as ethical implications, data extraction errors, international concerns, and analytical innovation; (IV) how existing judicial or litigation analytics can be translated to arbitrators and arbitration claims; (V) what machine learning and artificial intelligence can bring to analytics which has not already been discovered; (VI) how Federal Industry Regulatory Authority (FINRA) arbitration awards could be a key way to prove judicial and litigation analytics can apply to arbitrations; (VII) checking the amounts granted in FINRA arbitration awards with Benford's Law for statistical anomalies that might indicate a biased award was granted; (VIII) applying machine learning programs to FINRA arbitration

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¹² Guihot, *supra* note 3, at 452–54; Kasap, *supra* note 9, at 211–15.

¹³ George L. Paul & Jason R. Baron, *Information Inflation: Can the Legal System Adapt?*, 13 RICHMOND J.L. & TECH 10, ¶ 1–25 (2007) (discussing the need to use A.I. to ensure massive databases can be searched efficiently and effectively); Bennett Borden & Jason Baron, *Finding the Signal in the Noise: Information Governance, Analytics, and the Future of Legal Practice*, 20 RICH. J.L. & TECH. 7, ¶ 1–57 (2014); Jason Koebler, *Rise of the Robolawyers: How Legal Representation Could Come to Resemble TurboTax*, THE ATLANTIC (Apr. 2017), https://www.theatlantic.com/magazine/archive/2017/04/rise-of-the-robolawyers/517794/. *See generally* Maxi Scherer, *Artificial Intelligence and Legal Decision-Making: The Wide Open?*, 36 J. INT'L ARB. 539, 539–73 (2019).

awards to determine judicial analytics can be used on arbitral analytics; and (IX) a short summary conclusion.

II. BACKGROUND

The legal world is split into two general spheres of influence: civil law and common law systems. Within these systems, unique legal precedents have appeared and evolved over time into the modern legal system of today. However, people seek advantages over others in court claims. This started the "referral" phenomenon where a person would ask friends, co-workers, and other parties who they used as an attorney. Then, this person would decide whether to use that attorney based upon the review by their peers. But, as litigation analytics has definitively proven, this approach has significant drawbacks and flaws; plus, since a client is potentially risking their freedom or entire life savings in litigation or arbitration, they would likely feel analytics provides confirmation in their choice of legal representation.

Also, in the U.S. there were those in the early 19th century who wanted a more mathematically concrete way to measure an attorney's statistics.¹⁷ The first person to collect, analyze, and apply analytics to court decisions was Charles Haines, who reviewed and linked 15,000 public intoxication case outcomes to the personal traits of New York judges.¹⁸ Soon

¹⁴ What is the Difference Between Common Law and Civil Law?, WASH. UNIV. ST. LUIS SCH. L. (Jan. 28, 2014), https://onlinelaw.wustl.edu/blog/common-law-vs-civil-law/.

¹⁵ *Id*.

¹⁶ See e.g., Finding a Lawyer, JUD. COUNCIL CAL., https://www.courts.ca.gov/selfhelp-findlawyer.htm?rdeLocaleAttr=en (last visited Feb. 8, 2022) (advising the public to ask their friends, coworkers, and employers for attorney recommendations).

¹⁷ Charles Gove Haines, General Observations on the Effects of Personal, Political, and Economic Influences in the Decisions of Judges, 17 ILL. L. REV. 96, 96–116 (1922).

¹⁸ *Id*.

thereafter, Herman Pritchett analyzed and published a book on the dissent patterns of the U.S. Supreme Court.¹⁹ Even though judicial analytics was established early in the history of the U.S., there is a wealth of research in other countries not only on judicial analytics but arbitral analytics as well.²⁰ In summary, judicial analytics is nothing new, and today's explosion in research will only exponentially increase its reach and use as public awareness grows.

A. Types of Judicial Analytics Currently Used

As of 2020, there are numerous types of data tracked and followed by researchers and analytics companies such as Premonition, LLC.²¹ Given the number of complex approaches one

¹⁹ C. Herman Pritchett, THE ROOSEVELT COURT: A STUDY IN JUDICIAL POLITICS AND VALUES, 1937–1947 (Quid Pro Books, LLC 2014) (1948).

²⁰ Oleg Metsker, Egor Trofimov, Max Petrov, & Nikolay Butakov, Russian Court Decisions Data Analysis Using Distributed Computing and Machine Learning to Improve Lawmaking and Law Enforcement, 156 PROCEDIA COMPUT. SCI. 264, 264–73 (2019) (current Russian ML analysis of court cases); Кирилл Соснин, Предиктивная судебная аналитика: возможно ли знать решение судьи до его вынесения, VC.RU (Feb. 3, 2020), https://vc.ru/legal/104833-prediktivnaya-sudebnaya-analitikavozmozhno-li-znat-reshenie-sudi-do-ego-vyneseniya (last visited Nov. 2, 2020) (discussing Russian forensic analytics, another term for judicial analytics, as a way to predict litigation outcomes before a case is filed); Flora P. Kalalo & Kathleen C. Pontoh, The Use of Artificial Intelligence (AI) in Legal Framework for International Arbitration Practices in Indonesia, 472 ADVANCES SOC. SCI., EDUC. & HUMANITIES RSCH. 6, 6–10 (2020) (discussing the use of AI in arbitration cases held or involving Indonesian arbitration claims); Jena McGill & Amy Salyzyn, Judging by Numbers: How Will Judicial Analytics Impact the Justice System and Its Stakeholders?, 44 DALHOUSIE L.J. 249 (2021) (discussing the use of judicial analytics in Canadian court systems); M. A. Islam & M. Jahidul Haque, Evaluating Document Analysis with kNN Based Approaches in Judicial Offices of Bangladesh, 2018 SECOND INT'L CONF. ON COMPUTING METHODOLOGIES & COMMC'N, 646, 646-50 (2018) (discussing a brief overview of kNN applications on Bangladeshi courts); Nikolaos Aletras, Dimitrios Tsarapatsanis, Daniel Preotiuc-Pietro, & Vasileios Lampos, Predicting Judicial Decisions of the European Court of Human Rights: A Natural Language Processing Perspective, 2 PEERJ COMPUT. Sci., 1–19 (2016) (applying a bag of words (BOW) approach to judicial analytics). Litigation analytics can be divided into three categories: "(1) descriptive analytics–gathering, organizing, tabulating, and depicting data; (2) predictive analytics–using data to predict future courses of action; and (3) prescriptive analytics-recommendations on future courses of action." Borden & Baron, supra note 13, at 23; see also Weber, supra note 3, at 99–101, 105–14. However, AI can be used in any of these three categories for various purposes.

²¹ PREMONITION.AI, EVERYTHING YOU KNOW ABOUT LAWYER SELECTION IS WRONG (2016), https://premonition.ai/reports/; *Legal Analytics*, PREMONITION.AI, https://premonition.ai/ (last visited Nov. 1, 2020).

can infer from already collected and tracked data points, this paper will cover some of the more well-known data points garnering coverage by the larger legal research databases Lexis Nexis, Westlaw, and Bloomberg Law. However, this is by no means a comprehensive list of currently available data points as this paper would easily expand into several hundred pages and include research in over fifty languages.²²

To begin, this paper will cover the three main legal research databases, and after reviewing their analytics, the lesser known and more novel analytics will be discussed in greater detail since they have not been integrated into any current analytics database. First, the main databases can filter decisions by claim type (e.g. contracts, patents, etc.).²³ Second, you can further filter the results to show dispositive motions, discovery issues, orders, or other miscellaneous materials; you can then review the percentages of granted, denied, or partial status for each type of motion.²⁴ Third, you can further refine the most cited cases within the claim type or the dispositive motions, discovery issues, or orders.²⁵ Fourth, you can view all this data based upon a timeline, keyword, and the other courts potentially involved with the case or related cases.²⁶ Fifth, Bloomberg Law and Westlaw give more detail than Lexis Nexis by providing: the average filing-to-decision timeline and outliers the judge may have, case experience, full docket access with detailed analysis of assertions within each document, searchable filings, historical

²² See, e.g., Metsker, Trofimov, Petrov, & Butakov, supra note 20.

²³ LEXIS, *supra* note 5; WESTLAW, *supra* note 5; BLOOMBERG, *supra* note 5.

²⁴ *Id*.

²⁵ Id.

²⁶ *Id*.

analysis of parties and attorneys before the judge, expert witness challenges, appeal rates of judicial orders, and a Bloomberg Law exclusive news feed on that particular judge.²⁷

Turning to published papers, Daniel Chen by S.T.L.A. Mulders have publications with significant detail and analysis as well as more data points than most other papers. ²⁸

Mr. Chen covers a broad array of data points for U.S. federal court cases (circuit and district), the U.S. Supreme Court, U.S. asylum cases, the New Orleans district attorney's office, and French courts: (1) judicial influences such as priming, deontological, economics, mood, interpellation, masculinity, mimicry, visual cues, gambler's fallacy, snap judgements, time, implicit egoism, hierarchy, and judge versus prosecutor;²⁹ (2) a change in dissenting opinions by judges before a U.S. presidential election;³⁰ (3) a change in the precedent valence with the party appointing the judge;³¹ (4) rounding down of sentencing with the birthday effect;³² (5) the correlation of the local football team's winning or losing to the judge's decision;³³ (6) a third-party review of the masculinity of an attorney's voice before the U.S. Supreme Court with

²⁷ *Id*.

²⁸ Chen, *supra* note 9; Mulders, *supra* note 11.

²⁹ Chen, *supra* note 9, at 17–20.

³⁰ *Id.* at 18–21 (discussing how dissenting opinions systematically increase prior to an impending U.S. presidential election followed by a stark drop after the election cycle has completed).

 $^{^{31}}$ Id. at 19–22. The valence precedent used in cases can vary because of elections, and the regression table is further proof of the effect's veracity. Id.

³² *Id.* at 22, 24–25. The birthday effect only occurs on the defendant's birthday and no other surrounding day, and in French courts, the effect requires the defendant be present for the effect to appear. *Id.*

³³ *Id.* at 22–23. The football correlation disappears when a lawyer is present during an asylum hearing even with a win by the football team. *Id.* However, when the lawyer is not present, the football win increases asylum grants by 3.7%. *Id.*

correlations to judicial decisions;³⁴ (7) a correlation of implicit egoism when the first initial of the defendant's name matches the judge's first name initial;³⁵ and (8) predicting judicial outcomes based upon the judge's biographies.³⁶

Mulders focused on analytics reflected in Dutch court cases, but they likely exist at the same rates and frequencies in U.S. courts.³⁷ However, without further research and proof, these data points should be guidelines instead of dispositive requirements when deciding between attorneys.

Turning to Mr. Mulder's results, he analyzed 1,269 cases out of the roughly 15,000 cases collected by his crawler software.³⁸ These cases provide some remarkably interesting results which align, to a degree, with those of Mr. Chen's paper discussed previously: (1) attorneys with less than five years' experience out-performed attorneys with decades of experience;³⁹ (2)

³⁴ *Id.* at 23–29. The data shows a direct correlation between a lawyer's masculine voice and a judge's unfavorable decision as the masculinity rises. *Id.* Also, the masculinity is tied to the industry the lawyer represents with traditionally masculine industries such as mining, steel mills, oil and gas, manufacturing, lumber mills, heavy industries, etc. *Id.*

³⁵ *Id.* at 25–26. There is an increase of 8% longer sentences when the first initial, second letter of the name, full name match between the judge and the defendant, or the defendant's first letter of the name is rare (e.g., x, z, etc.). *Id.* Racially discriminatory labels such as "negro" amplify this effect with even more severe sentences. *Id.*

³⁶ *Id.* at 36–40. A judge moving from the left to the right on the U.S. political spectrum can have an 8% to 32% change in politically motivated ruling based upon the precedent and phrase usage; economics usage; and vote polarization with electoral dissent. *Id.*

³⁷ Mulders, *supra* note 11, at 1–45.

³⁸ *Id.* at 30.

³⁹ *Id.* at 16 (citing Shozo Ota, *Quality of Lawyers in Civil Litigation in the Era of Drastic Changes in Legal Education and Lawyer Population in Japan*, XVIII ISA WORLD CONG, SOCIO. (2014)); Ronald F. Wright & Ralph A. Peeples, *Criminal Defense Lawyer Moneyball: A Demonstration Project*, 70 WASH. & LEE L. REV. 1221 (2013). Younger attorneys tend to work harder, have better education, and suffer from "survivor bias" where only the winners survive the culling of young associates at law firms. Mulders, *supra* note 11, at 16.

membership in legal profession specialization boards increases the win rate;⁴⁰ (3) a potential win difference based upon gender;⁴¹ and (4) a home field advantage.⁴²

Both papers indicate analytics are here to stay, and every attorney should be checking their own analytics for strengths and weaknesses. In fact, there are even more analytics not only advancing the field, but changing attorneys into professional sports players who can be "traded" for people with certain required strengths.⁴³

As for other analytics, there are an almost unlimited number of ways to analyze litigation; however, there are some notable analytics worth mentioning, such as signs of increased litigation resulting in higher damages against an initial group of criminals during the first year of new statutes adoption in the Russian Federation⁴⁴—a clear link between longer prison sentences and

⁴⁰ Mulders, *supra* note 11, at 19–21. However useful this might be, there are scarcely any studies or research on this subject, so it should be taken with a grain of salt since it cannot guarantee a win or even receiving better cases. *Id.*

⁴¹ *Id.* at 20. In Dutch courts, female plaintiffs' attorneys have an 8% win rate advantage over males in the same position, and this advantage is amplified when the client is also female. *Id.* at 37–38. The author suggests the reason females win more often is the leniency of male judges, different risk-taking strategies, and a higher drop-out rate for female attorneys—survival of the fittest—altering the statistical outcome. *Id.*

⁴² *Id.* at 20–21. Generally, attorneys from the same district will enjoy an advantage since they are regulars within their local district courts, but this area is under studied and ripe for further research.

⁴³ Nancy Rapoport, *Client-Focused Management of Expectations for Legal Fees in Large Chapter 11 Cases*, 28 AM. BANKR. INST. L. REV. 39, 85–88 n.166 (2020) (citing Michael Rappa, Theodore Eisenberg, Joseph W. Doherty, Christopher Zorn, Elizabeth H. Johnson, Silvia H. Silverstein, Larry Bridgesmith, Owen Byrd, John Boswell, John W. O'Tuel, & Rob Tiller, *The Evolving Role of the Corporate Counsel: How Information Technology Is Reinventing Legal Practice*, 36 CAMPBELL L. REV. 383, 443 (2013)). For example, you may want certain attorneys for only dispositive motions and others for discovery disputes, but building a legal team is likely a key part of winning future disputes before particular judges or arbitrators.

⁴⁴ Metsker, Trofimov, Petrov, & Nikolay, *supra* note 20, at 267–70 (analyzing litigation outcomes based upon the implementation of Russian fire code statutory changes under Russian civil law).

the denial of relapse punishment if the criminal admits they made a mistake,⁴⁵ the judicial responsiveness to briefs or other filings with the court,⁴⁶ the prediction of clerks writing the opinions of judges based upon word usage,⁴⁷ the judge's preference to other opinions written by their favorite judges,⁴⁸ a case's passing rate based upon a judge's historical behavior in similar cases,⁴⁹ the rate of appeal for affirming or rejecting the judge's ruling,⁵⁰ gender and race outcome analysis,⁵¹ the "friendliness" of each justice,⁵² the use of a judge's defensive language to express

⁴⁵ *Id.* at 270–72. If a reformed person relapsed by committing another crime, then the legal statutory changes made a guilty plea equate to a lower punishment instead of extensive litigation through the courts under Russian civil law. *Id.*

⁴⁶ Oldfather, Bockhorst, & Dimmer, *supra* note 11, at 1192–1242. In this instance, the author tested how the judiciary behaved when a motion or other filing influenced the legal precedent the court would apply to the facts provided by the party, and whether the court sufficiently applied the facts to the case. *Id*.

⁴⁷ *Id.* at 1207–08 (citing Stephen J. Choi & G. Mitu Gulati, *Empirical Measures of Judicial Performance: Which Judges Write Their Opinions* (*And Should We Care*)?, 32 FLA. STATE U. L. REV. 1077, 1107–21 (2005)); Keith Carlson, Michael A. Livermore, & Daniel Rockmore, *A Quantitative Analysis of Writing Style on the U.S. Supreme Court*, 93 WASH. U. L. REV. 1461, 1497–1508 (2016); *see* Todd C. Peppers & Christopher Zorn, *Law Clerk Influence on Supreme Court Decision Making: An Empirical Assessment*, 58 DEPAUL L. REV. 51 (2008). *See also* Paul J. Wahlbeck, James F. Spriggs II, & Lee Sigelman, *Ghostwriters on the Court? A Stylistic Analysis of U.S. Supreme Court Opinion Drafts*, 30 AM. POL. RSCH. 166, 175–77 (2002). The analytical ability to predict authors based upon the writing style and words used has resulted in the ability to determine and rank which judges write their own opinions, and which heavily rely upon their clerks for writing with surprising accuracy. Oldfather, Bockhorst, & Dimmer, *supra* note 11, at 1207–08.

⁴⁸ McGill & Salyzyn, *supra* note 20, at 5 (citing PREMONITION, JUDICIAL DASHBOARD (2020), https://premonition.ai/wp-content/plugins/wonderplugin-pdf-embed/pdfjs/web/viewer.html?disabledownload=1&file=https%3A%2F%2Fpremonition.ai%2Fwp-content%2Fuploads%2F2018%2F01%2FPA036-Judicial-Dashboard-Sales-Sheet3.pdf).

⁴⁹ *Id*.

⁵⁰ *Id*.

⁵¹ *Id*.

⁵² Carlson, Livermore, & Rockmore, *supra* note 47, at 1479–81. "Friendliness" relates to a positive or negative word used by a U.S. Supreme Court Justice when writing their opinion. *Id*.

weakness on a particular subject,⁵³ the similarity in writing styles of U.S. Supreme Court Justices working together—or in a similar temporal period,⁵⁴ the use of numerical analysis on financials provided in cases to determine if fraud has taken place,⁵⁵ the use of a bag of words to determine the weight certain words have on the ruling by a court,⁵⁶ the influence on arbitrators by other related arbitrators with decisions based upon social network connections,⁵⁷ party win analysis via case topic key words,⁵⁸ and many more analytics worth further investigation.

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⁵³ *Id.* at 1481–84 (citing Lance N. Long & William F. Christensen, *When Justices (Subconsciously) Attack: The Theory of Argumentative Threat and the Supreme Court*, 91 OR. L. REV. 933, 935–36 (2013)). "Defensiveness" words were found to be statistically more common with dissents than in the majority opinion at 0.18% and 0.12% respectively. *Id.*

⁵⁴ *Id.* at 1484–91 (finding Justices working together within the same decade were remarkably similar in writing styles compared to Justices working further and further away from this decade).

⁵⁵ J. Carlton Collins, *Using Excel and Benford's Law to Detect Fraud*, J. ACCT. (Apr. 1, 2017), https://www.journalofaccountancy.com/issues/2017/apr/excel-and-benfords-law-to-detect-fraud.html.

⁵⁶ Aletras, Tsarapatsanis, Preotiuc-Pietro, & Lampos, *supra* note 20, at 1, 12–16; *see* Masha Medvedeva, Michel Vols, & Martijn Wieling, *Judicial Decisions of the European Court of Human Rights: Looking into the Crystal Ball*, PROC. CONF. ON EMPIRICAL LEGAL STUDS. EUR. 1, 18 (2018). Aletras, Tsarapatsanis, Preotiuc-Pietro, and Lamps found significant weight could be assigned to certain words of up to 15.70, down to -17.40, and utilizing this method, a predictive accuracy for the European Court of Human Rights of 79%. Aletras, Tsarapatsanis, Preotiuc-Pietro, & Lampos *supra* note 20, at 1, 12–16.

⁵⁷ Malcolm Langford, Daniel Behn, & Runar H. Lie, *The Revolving Door in International Investment Arbitration*, 20 J. INT'L ECON. L. 301, 309–14, 321 (2017) (finding a complex network of arbitrators, some of whom were acting as counsel in one case and as an arbitrator in another "double hatting," could be influenced by their social network of arbitrators when writing a brief or drafting an award).

⁵⁸ Amarnath Gupta, Alice Z. Wang, Kai Lin, Haoshen Hong, Haoran Sun, Benjamin L. Liebman, Rachel E. Stern, Subhasis Dasgupta, & Margaret E. Roberts, *Toward Building a Legal Knowledge-Base of Chinese Judicial Documents for Large-Scale Analytics*, 320 LEGAL KNOWLEDGE & INFO. SYS. 135, 139–43 (2017).

Furthermore, governments worldwide are beginning to take notice of litigation analytics.⁵⁹ One pertinent example is Legal-Net for the Israeli Judicial Branch.⁶⁰ Legal-Net created significant productivity efficiencies throughout the entire judicial system, but more importantly, it allowed for extreme levels of transparency on every judge using the system.⁶¹ Additionally, this transparency allowed for closer monitoring by presidents of courts, the Chief Justice, Administration of the Court, and the Ministry of Justice.⁶² Legal-Net will automatically read judicial orders, timelines for rulings, unusual writing patterns, and many more analytics that can be used by monitoring groups for judicial behavior that does not match their peers.⁶³ Nonetheless, this provides ample opportunity for malevolent parties to burn judges instead of using it for benevolent purposes.⁶⁴ For example, it might be used by governments to ensure judges do not vary their opinions from the status quo or to prevent political change by citizens since judges know their work is being watched very carefully. Thus, the system wields neverbefore-seen and unprecedented power over the judicial branch.⁶⁵

⁵⁹ See, e.g., Amnon Reichman, Yair Sagy, & Shlomi Balaban, From a Panacea to a Panopticon: The Use and Misuse of Technology in the Regulation of Judges, 71 HASTINGS L.J. 589, 591 (2020).

⁶⁰ *Id.* Legal-Net was designed to be a cloud-based judicial administrative software for intaking, filing, reviewing, and generally managing all court cases for the Magistrate and District courts of Israel. *Id.* at 598

⁶¹ *Id.* at 594–95.

⁶² *Id*.

⁶³ *Id.* at 594–95, 625–27 (describing the judge's standard flow-chart process for cases which, when normal tolerances are violated, alerts the relevant oversight parties and the litigants to ensure the justice system prevents deviation from judicial standards).

⁶⁴ *Id.* at 594–95.

⁶⁵ *Id.* at 592.

In contrast, the United States has an extremely fragmented legal administrative software system that can vary from county to county within the same state.⁶⁶ Thus, a unified approach would likely bring similar efficiencies enjoyed by the Israeli Judicial Branch.

In summary, the background of litigation/judicial analytics stretches back over 100 years, and it is only the method of collecting and analyzing the data that has evolved.

III. ISSUES WITH LITIGATION, JUDICIAL, AND ARBITRAL ANALYTICS

With such a rich background, there are many opportunities for misconduct from individuals, companies, other entities, national governments, and foreign actors such as foreign governments. Therefore, it would be worth a brief coverage of what can be expected, what has already occurred, and the potential issues litigation, judicial, and arbitral analytics may encounter as the field expands over the coming decade and beyond.

A. ETHICAL ISSUES CONFRONTING ARBITRATION INSTITUTIONS

First, since this paper is setting the stage for the application of judicial analytics applied to arbitrations, it would be wise to discuss the ethical issues modern arbitration institutions and U.S. courts will likely encounter. To begin, both JAMS and the American Arbitration Association (AAA), who oversee thousands of arbitrations throughout the U.S. every year, provide a code of ethics or guidelines for arbitrators.⁶⁷ However, this process is riddled with

⁶⁷ Jud. Arb. & Mediation Servs., Comprehensive Arbitration Rules and Procedures Rule 15 (2014) [hereinafter JAMS Rules], https://www.jamsadr.com/rules-comprehensive-arbitration/; Am. Arb. Ass'n, Commercial Arbitration Rules and Mediation Procedures Rule 12 (2013) [hereinafter AAA Rules], https://www.adr.org/sites/default/files/Commercial%20Rules.pdf.

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⁶⁶ Natalie Gomez-Velez, *Internet Access to Court Records – Balancing Public Access and Privacy*, 51 Loy. L. Rev. 365, 367–69 n.3 (2005).

holes when arbitral analytics are applied since analytics is not even considered when arbitrators are appointed in cases.⁶⁸

This is best exemplified with the application of a well-known case where the court found there was a violation of the basic neutrality standards an arbitrator must abide by in *Hooters of America, Inc. v. Phillips*.⁶⁹ When arbitral analytics are applied to this case, you can easily circumvent the "arbitration neutrality" the court is attempting to uphold. A key use of arbitral analytics would be to tilt the arbitrator list, which could be provided by JAMS or AAA, to ensure the arbitration-institution-maintained list contained only business friendly arbitrators; have experience representing employers; grant unusually high dismissal rates or summary judgements in favor of the employer; take longer to decide than other arbitrators in their field; have litigated employer friendly cases; are male, female, or a specific race with a known bias towards another race, gender, or other protected classes; political standing; known family members of arbitrators who might have undergone similar treatment to what the arbitrator is deciding upon; and many more analytics the average attorney or client lack even basic knowledge of or access to data

⁶⁸ Arbitrator Selection, AM. ARB. ASS'N, https://www.adr.org/ArbitratorSelection (last visited Sept. 6, 2021).

⁶⁹ Hooters of America, Inc. v. Phillips, 173 F.3d 933 (4th Cir. 1999) (discussing the Hooters-maintained arbitration standards were unconscionable and void for public policy reasons); *see also* Commonwealth Coatings Corp. v. Cont'l Cas. Co., 393 U.S. 145, 148–50 (1968); Murray v. UFCW Int'l, Local 400, 289 F.3d 297, 304–05 (4th Cir. 2002); Penn v. Ryan's Family Steak Houses, 269 F.3d 753, 757 (7th Cir. 2001); Gullett v. Kindred Nursing Ctrs. W., LLC, 390 P.3d 378, 384–85 (Ariz. Ct. App. 2017); Harold Allen's Mobile Home Factory Outlet, Inc. v. Butler, 825 So. 2d 779, 784 (Ala. 2002). Hooters corporate required employees to sign an unread arbitration provision, advanced notice of their claims, Hooters can choose not to file responsive pleadings, the employee cannot raise any further claims outside of the initial statement of claim, Hooters can move for dismissal of the claim before a hearing is completed, the employee cannot file for summary judgement, the employee does not have the right to record the hearings, Hooters can modify the rules at any time, Hooters can cancel the arbitration provision with thirty days' notice while the employee is not afforded this right, and a Hooters approved and maintained arbitrator list is the only arbitrators an employee can choose from. Hooters of America, Inc. v. Phillips, 173 F.3d at 935–40.

which may show this bias.⁷⁰ Therefore, the AAA Code of Ethics, based upon the Hooters example, would be violated without the arbitrator's, the arbitration institution's, or the parties' knowledge or consent to such blatant violations since the Hooters-maintained arbitrator list could be skewed to only include arbitrators who have favorable analytics to the employer.⁷¹

B. ISSUES WITH THE APPLICATION OF JUDICIAL/LITIGATION ANALYTICS TO ARBITRATORS

Expanding upon the topic of bias, arbitration awards are also generally confidential and are not published.⁷² Thus, many larger law firms maintain confidential databases of which arbitrators rule in their favor and some basic reasoning as to why this occurs.⁷³ This private data is not shared with any third party, so the firms believe it can give them a winning edge with supposedly "neutral" arbitrations.⁷⁴ Furthermore, the confidential nature of awards with sparse sharing by parties before the arbitration panel further complicates the intent of this paper to show a direct correlation between an attorney's or judge's publicly available analytics and those of the arbitral analytics, which should be the same.

⁷⁰ JAMS Rules, *supra* note 67; AAA Rules, *supra* note 67.

⁷¹ AM. ARB. ASS'N, THE CODE OF ETHICS FOR ARBITRATORS IN COMMERCIAL DISPUTES, Canon I–X (Mar. 1, 2004) [hereinafter AAA Code of Ethics], https://www.adr.org/sites/default/files/document_repository/Commercial_Code_of_Ethics_for_Arbitrator s_2010_10_14.pdf. I would go as far as to say AAA and JAMS should provide the arbitral analytics whenever an arbitrator from their respective institutions is being chosen in a case. This would aid in ensuring a transparent selection process is undertaken, and it would prevent either side from gaining an unfair advantage the other side is unaware of. Thus, both JAMS and AAA should amend their ethics rules to include a new mandatory section to cover arbitral analytics.

⁷² Catherine Rogers, *Arbitrator Intelligence: From Intuition to Data in Arbitrator Appointments*, 11 N.Y. DISP. RESOL. LAW. (forthcoming Spring 2018).

⁷³ Telephone Interview with Toby Unwin, Chief Innovation Officer at Premonition.ai (Sept. 22, 2020) [hereinafter Toby Unwin Interview].

⁷⁴ *Id*.

In addition to the confidentiality of awards, most judges, attorneys, arbitrators, and mediators are resistant to change.⁷⁵ This recalcitrant belief towards analytics is unwarranted and will eventually result in a scenario like the one described above in *Hooters* becoming a forgone conclusion over the next decade. It is this author's opinion that analytics should be embraced by the legal profession, with guardrails, to not only ensure the rule of law, but also, to reaffirm the neutrality—with scientific evidence—of the attorneys who swore to uphold the law in their respective countries.⁷⁶

C. ISSUES WITH EXTRACTING DATA FROM COURT DATABASES

When researching and attempting to create my own analytics database, I ran into a common problem all other papers in the litigation, judicial, and arbitration (lit-jud-arb) analytics space also suffered from; the complex nature of extracting data from a multitude of online databases into an analyzable, standard format.⁷⁷

The first hurdle any data collection encounters is cost, and when cost is involved, it will likely result in a sample collection of a court database instead of the full population given the potential for a per page cost easily exceeding \$100,000.00 when thousands of pages may be

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⁷⁵ Alyson Carrel & Noam Ebner, *Mind the Gap: Bringing Technology to the Mediation Table*, 2019 J. DISP. RESOL. 1, 7–8 (2019). I once knew an attorney who, in 2012, still used an electric typewriter from the 1980's. What took another attorney less than an hour to research, draft, and get approval from the partner took this attorney over four hours to complete!

⁷⁶ The failure to embrace litigation/judicial/arbitral analytics brings with it a colossal risk of economic instability, social unrest, and other negative economic consequences we have yet to understand or discover. *See* Maryclaire Dale, *Russian Hack Brings Changes, Uncertainty to US Court System*, ASSOCIATED PRESS, (Jan. 21, 2021), https://apnews.com/article/coronavirus-pandemic-courts-russia-375942a439bee4f4b25f393224d3d778.

⁷⁷ Ben-Ari, Frish, Lazovski, Eldan, & Greenbaum, *supra* note 9, at 48–55; Addison Cameron-Huff, *Why Google Can't Build A Case Law Search Engine in Ontario*, CAMERONHUFF (Feb. 11, 2014), https://www.cameronhuff.com/blog/ontario-case-law-private/; Mulders, *supra* note 11, at 29–31; McGill & Salyzyn, *supra* note 20, at 7–9.

requested.⁷⁸ Thus, when developing a database, the researcher or attorney must take into account the cost of research and what the consequences of using incomplete data for a case or their legal thesis.

Second, all document and web scraping programs generate imperfect copies with errors.⁷⁹ When a court website uploads any kind of document, it could be as an image, a non-readable pdf, or numerous other formats that make it difficult to download, scan, and read for any program. Thus, any collected data is bound to have numerous errors which will affect the accuracy and depth of any patterns any researcher can discern from the data. Furthermore, the vastly different programs and databases used by PACER and state courts throughout the U.S. can complicate, even on a limited scale, web scraping and all other data collection which can result in errors.⁸⁰

Third, the age of a case can be a huge factor when it comes to analytics because lower state courts generally do not save older cases or dockets beyond ten years.⁸¹ In fact, age plays a pivotal role in why older attorneys not only hold an edge but are also resistant to the promise of

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⁷⁸ Michael Lissner, *As Bloomberg Law Imposes Caps on PACER Access, PACER Must Support Academics*, FREE LAW PROJECT (Apr. 4, 2020), https://free.law/2020/04/04/as-bloomberg-law-imposes-caps-on-pacer-access-pacer-must-support-academics/ (reporting Bloomberg Law will now limit legal researchers to a maximum of \$1,500.00 in free legal documents before limiting access); Vacek Case Outcome, *supra* note 11, at 50–51 (discussing fee waivers for educational and research purposes of PACER fees for federal court docket searches).

⁷⁹ Mulders, *supra* note 11, at 27; Deeks, *supra* note 4, at 642; McGill & Salyzyn, *supra* note 20, at 16. Web scraping is a program used to pull data such as text from a website to index and categorize into a database for further analysis.

⁸⁰ Patrick Flanagan & Michelle Hook Dewey, *Where Do We Go From Here? Transformation and Acceleration of Legal Analytics in Practice*, 35 GA. ST. U.L. REV. 1245, 1257–258 (2019); PREMONITION.AI, PREMONITION GUIDE TO COURT DATA 1–23 (2017) [hereinafter PREMONITION COURT DATA], https://premonition.ai/reports/.

⁸¹ SUP. CT. ARIZ., SUPERIOR COURT RECORDS RETENTION AND DISPOSITION, ARIZ. CODE JUD. ADMIN. § 3–402 (C) (2006); JUD. COUNCIL CAL., TRIAL COURT RECORDS MANUAL 1, 3–117 (2020); OFF. SEC'Y STATE, LOCAL GOVERNMENT COMMON RECORDS RETENTION SCHEDULE 1, 6–38 (2020). *See generally*, NAT'L CTR. FOR STATE CT., *Court Retention Schedules*, https://www.ncsc.org/topics/technology/records-document-management/state-links2 (last visited Jan. 29, 2021).

analytics. Solder attorneys have labored the same way they always have for the past two centuries, and since no records are retained of their past success or failure, the old attorneys' records are wiped clean the same as a new attorney who just passed the bar. Therefore, they feel there is no reason to change or to adopt analytics since everything is business as usual, and analytics is just another phase they can wait out until it passes. However, this is not the case, and it presents an enormous issue that analytics will be plagued with until most attorneys who practiced prior to 1989 have retired since they present a wild card without much analytical history beyond the late 1990's. Since this problem will persist, it will affect any analytics used against older attorneys who may have more experience with the judge, arbitrator, or mediator presiding over the case; thus, all analytics should take this into account and should warn its readers of this risk when applying their findings to the entire attorney population.

Fourth, analytics based upon AI is a relatively new field with sparse research compared to more established fields such as chemistry or political science, so it would be premature to not account for unknown variables, patterns, or new data sources which might fundamentally shift how litigation, arbitration, and mediation is analyzed. Thus, no paper on this subject is complete without a small disclaimer that new data could lead to a superior way to learn and approach analytics.

Finally, many states still refuse to upload court decisions, documents, and other evidence to online databases.⁸³ This can be for various reasons, but it results in incomplete data and gaps

82 McPeak, *supra* note 10, at 471–73.

⁸³ Kirk C. Jenkins, *Making Sense of the Litigation Analytics Revolution*, A.L.I. 1, 4 (2017); Flanagan & Dewey, *supra* note 80.

in any analytical conclusions inferred from research.⁸⁴ In conclusion, when reviewing analytics for arbitrators and judges, we must account for all the non-published legal filings which are not online at the state level or from private arbitration when inferring patterns from databases.

D. THE INTERNATIONAL REACTION TO LITIGATION ANALYTICS

In addition to the many extraction issues any analytics must overcome, analytics are beginning to catch the attention of international bar associations and governments who fear it might be used for nefarious purposes.⁸⁵

The first and best example is the French Republic's relatively new law banning judicial analytics based upon court decisions.⁸⁶ Once the Justice Reform Act was adopted, it required anonymity to any party named in the case; the banning of any analytics for French judges or court clerks; and punishment up to five years in prison if a party is caught applying any kind of analytics to an identifiable judge's court decisions.⁸⁷ Furthermore, this law broadly covers academic research, legal technology corporations, law firms, and the general public for any kind of publicly available court information.⁸⁸ However, the Justice Reform Act does not ban

⁸⁴ Jenkins, *supra* note 83.

⁸⁵ Grégoire Triet & Gide Loyrette Nouel, *Legal Tech, in View of the French Judicial "Analytics Ban."*, FICPI 18th F. 1, 1–16 (Oct. 11, 2019), https://ficpi.org//uploads/files/IP PM Session 7.3 - Triet .pdf.

⁸⁶ Loi 2019–222 du 23 mars 2019 de programmation 2018–2022 et de réforme pour la justice [Law 2019–222 of March 23, 2019 on the programming and reform for justice], LéGIFRANCE: JOURNAL OFFICIEL DE LA RÉPUBLIQUE FRANÇAISE [J.O.] [OFFICIAL GAZETTE OF FRANCE], Mar. 24, 2019, p. 15–16 [hereinafter Justice Reform Act], https://www.legifrance.gouv.fr/eli/loi/2019/3/23/JUST1806695L/jo/article_33; McGill & Salyzyn, *supra* note 20, at 1 (citing the Justice Reform Act); Jason Tashea, *France Bans Publishing of Judicial Analytics and Prompts Criminal Penalty*, A.B.A. J. (June 7, 2019, 12:51 PM CDT), https://www.abajournal.com/news/article/france-bans-and-creates-criminal-penalty-for-judicial-analytics; *see also* Stewart & Stuhmcke, *supra* note 7, at 82.

⁸⁷ McGill & Salyzyn, *supra* note 20, at 1–2 (citing *France Bans Judge Analytics*, 5 *Years in Prison for Rule Breakers*, ARTIFICIAL LAW. (June 4, 2019), https://www.artificiallawyer.com/2019/06/04/france-bans-judge-analytics-5-years-in-prison-for-rule-breakers/); Triet & Nouel, *supra* note 85.

⁸⁸ McGill & Salyzyn, *supra* note 20, at 1–2.

litigation analytics when only the judicial entity is analyzed; thus, analytics is permitted when individual judges are not included.⁸⁹ The reasoning behind the Justice Reform Act was to limit judicial profiling based upon "questionable correlations," safety of the judicial branch, partiality allegations which may cause serious litigation issues, and to prevent forum shopping from becoming a common legal strategy.⁹⁰ In conclusion, the French government was concerned analytics could be used for nefarious purposes by the public, so it decided a blanket ban would be the ideal way to address the issue.⁹¹

Second, arbitral and litigation analytics are currently used by governments to ensure their interests are protected when international arbitration panels, arbitrations conducted by the United Nations, World Trade Organization (WTO) disputes, and treaties between countries which might include unique arbitration provisions similar to the New York Convention of 1958 are involved. In fact, stylometric analysis of WTO arbitration decisions has uncovered members of the Secretariat, instead of arbitrators, contribute significantly to the drafting of arbitration decisions. In one pertinent case cited by Damien Charlotin, Russia likely became the first

⁸⁹ Triet & Nouel, *supra* note 85, at 11–13 (discussing the judicial analytics ban, allowed analytics, and arguments for or against the ban on analytics).

⁹⁰ *Id.* at 11–13.

⁹¹ *Id.* at 1–16; McGill & Salyzyn, *supra* note 20, at 1–2; Tashea, *supra* note 86.

⁹² Alschner, *supra* note 4, at 217–31; Deeks, *supra* note 4, at 583–84, 594–95, 626 (discussing the development of data analytics; arbitral analytics; and treaty analytics in the European Union; Russia; China; Japan; the U.S.; and other countries; plus, its application to government arbitrations and treaty negotiations); Jeffery Commission & Giulia Previti, *The Increasing Use of Data Analytics in International Arbitration*, N.Y. L.J. (Nov. 20, 2020, 2:30 PM EST), https://www.law.com/newyorklawjournal/2020/11/20/the-increasing-use-of-data-analytics-in-international-arbitration/?slreturn=20210009011321; *Convention on the Recognition and Enforcement of Foreign Arbitral Awards*, U.N. CONF. INT'L COM. ARB. 1, 1–7 (July 6, 1958), http://www.newyorkconvention.org/11165/web/files/original/1/5/15432.pdf.

⁹³ Deeks, *supra* note 4, at 625–33 nn.273–74 (citing DAMIEN CHARLOTIN, IDENTIFYING THE VOICES OF UNSEEN ACTORS IN INVESTOR-STATE DISPUTE SETTLEMENT 392–426 (Freya Baetens eds., 2019)

country to use analytics to aid in setting-aside an arbitration award based upon billable hours, but stylometric analysis would have likely found the same result or better after further research found the arbitrator's award was mostly written by the Secretariat instead of the full arbitration panel.⁹⁴

Finally, international legal scholars are exploring the ethical issues presented by litigation, judicial, and arbitral analytics. ⁹⁵ In Australia, Pamela Steward and Anita Stuhmcke provide an excellent starting point for ethical guidelines on judicial analytics compared to the outright ban by the French government. ⁹⁶ Steward and Stuhmcke suggest the courts should regulate and provide ethical guidelines similar to those found in Australian medical services such as the National Statement on Ethical Conduct in Human Research to aid in preserving the rule of law and in preventing "low correlation" analytics from interfering with the judicial or arbitral decision making process. ⁹⁷ McGill and Salyzyn of Canada also contend that analytics aids in

[[]hereinafter Charlotin Investor Dispute Settlement]); Damien Charlotin, *Who Writes WTO Panel and AB Reports? A Tentative Stylometric Analysis*, Medium (May 1, 2018) [hereinafter Charlotin Stylometric Analysis], https://medium.com/@damien.charlotin/who-writes-wto-panel-and-ab-reports-a-tentative-stylometric-analysis-565c18f0491d).

⁹⁴ Yukos Universal Ltd. (Isle of Man) v. The Russian Fed'n, PCA Case Repository 2005-04/AA227 (2020), https://www.italaw.com/cases/1175; Deeks, *supra* note 4, at 625–33 nn.273–74 (citing Charlotin Stylometric Analysis, *supra* note 93); RYAN WHALEN, COMPUTATIONAL LEGAL STUDIES: THE PROMISE AND CHALLENGE OF DATA-DRIVEN RESEARCH 57–60 (Ryan Whalen eds., 2020).

⁹⁵ Stewart & Stuhmcke, supra note 7, at 82–87; McGill & Salyzyn, supra note 20, at 2–3, 22–27.

⁹⁶ Stewart & Stuhmcke, *supra* note 7, at 86–87.

⁹⁷ *Id.* at 86 n.30 (citing NAT'L HEALTH AND MED. RSCH. COUNCIL, NATIONAL STATEMENT ON ETHICAL CONDUCT IN HUMAN RESEARCH 1, 9–99 (2018) [hereinafter NHMRC ETHICS]), https://www.nhmrc.gov.au/about-us/publications/national-statement-ethical-conduct-human-research-2007-updated-2018#block-views-block-file-attachments-content-block-1; AUSTL. GOV'T, DEP'T OF INDUS., SCI., ENERGY, AND RES., *AI Ethics Principles*, https://www.industry.gov.au/data-and-publications/building-australias-artificial-intelligence-capability/ai-ethics-framework/ai-ethics-principles (last visited Sept. 6, 2021)). More to the point, the ethical guidelines found in sections two through five grant researched parties the right to certain discoveries found in the research (e.g. Judge Smith analytics show a bias towards a disabled plaintiff). NHMRC ETHICS, *supra*. This will help a judge know when

establishing the rule of law, but advocate in addition for ethical guardrails and regulations to protect against publishing low correlation or poor quality analytics to the general public to review and apply to the judicial branch.⁹⁸ However, they are unsure of which regulatory body should pass laws or establish rules for the analytics industry to review and in turn, recommend a non-profit public legal organization that should "develop high quality, free judicial analytics tools for public use."⁹⁹

In summary, international lawyers and governments around the world are actively using analytics to better determine which path they should take with their own society and how to approach international litigation, arbitration, or treaty negotiation. However, this field is still in its infancy, so any solid conclusions would be premature. 101

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something is published on their rulings, and it will prevent poor or inaccurate data from contaminating their reputation since they could challenge the findings. *Id.* Furthermore, highly sensitive research on cases involving national security (e.g. defense contractor litigation) would be immensely helpful to the U.S., but this should only be shared with Congress. *Id.* Finally, if the research does show a serious issue with a judge, should parties be notified of the ramifications this research might have on their judge? *Id.* The numerous avenues for moral, ethical, and political issues associated with lit-jud-arb analytics are nearly endless, so this question deserves hundreds of papers just to explore these issues.

⁹⁸ McGill & Salyzyn, *supra* note 20, at 22–24. Perhaps the Israeli Legal-Net company would be a great place for CanLII or another non-profit Canadian organization to begin their search for publicly available judicial analytics reporting tool. Reichman, Sagy, & Balaban, *supra* note 59, at 591; CANLII, *What's CanLII*, https://www.canlii.org/en/info/about.html (last visited Sept. 6, 2021).

⁹⁹ McGill & Salyzyn, *supra* note 20, at 24.

¹⁰⁰ Alschner, *supra* note 4, at 217–31; Deeks, *supra* note 4, at 583–84, 594–95, 625–33 nn.273–74; McGill & Salyzyn, *supra* note 20, at 2–3, 22–27; Reichman, Sagy, & Balaban, *supra* note 59, at 591; Stewart & Stuhmcke, *supra* note 7, at 82–87; Triet & Nouel, *supra* note 85, at 11–13; WHALEN, *supra* note 94.

¹⁰¹ KNOWLEDGE @ WHARTON, *The Next Legal Challenge: Getting Law Firms to Use Analytics*, UNIV. OF PA.: WHARTON (Nov. 22, 2019), https://knowledge.wharton.upenn.edu/article/getting-law-firms-to-use-analytics/.

E. INNOVATION BY INTERNATIONAL ANALYTICS COMPANIES

Turning to international litigation analytics, there are several major companies who can compete outside of the two largest in the U.S. This list is by no means complete since smaller start-ups and other companies would take up several papers on their own.

First, the largest competitor is Caselook.¹⁰² This Russian company has some of the best and most detailed analytics on the market that, in many cases, can match or surpass companies in the U.S. for the sheer volume of data and analytics they can offer.¹⁰³ Caselook's depth and expansion into Europe and the U.S. is likely only a few years away and will produce stiff competition for domestic litigation analytics firms.¹⁰⁴

As for China, Legal Miner has emerged as an industry leader with their application of data extraction, semantic analysis, machine learning prowess, and AI pattern recognition to the fragmented Chinese legal system. Although not as advanced as Premonition or Caselook, they

 $^{^{102}}$ CASELOOK, https://caselook.ru/ (last visited Sept. 6, 2021). For \$\text{P}48,000.00\$, roughly \$600.00 USD, annually for a complete subscription to this service. *Id*.

¹⁰³ CASELOOK, *supra* note 102; PRAVOTECH.RU, https://pravo.tech/ (last visited Sept. 6, 2021); *see also* Pravo Tech, *Casebook* — *cucmema для мониторинга судебных дел и проверки контрагентов*, YOUTUBE (Sept. 3, 2017) [hereinafter *Casebook Demo*], https://www.youtube.com/watch?v=WBf9PkT-YLQ&feature=emb_logo. The list of analytics is extensive, and it includes everything you would expect based upon my research: lawyer analytics (filing timelines, affiliations, writing styles, litigation tactics, etc.); company/party research (affiliations, on-going litigation or arbitration claims, bankruptcy watch for subsidiaries or parent companies, political risks, past legal counsel, litigation tactics, corporate structure, etc.); arbitration statistics (past arbitrators, win-loss rates, filing history, amounts awarded, legal tactics, pending cases, affiliations with the arbitrator between parties, prior counsel used with arbitrators, stylometric analysis of arbitrators and legal counsel, etc.); affiliation graph between companies, parties, judges, arbitrators, witnesses, and other third parties; financial analysis of opposing counsel and their clients (companies, individuals, and other parties); and any changes for arbitrators, judges, legal counsel, or parties in any on-going case or any other related case. PRAVOTECH.RU, *supra*; *Casebook Demo*, *supra*; CASELOOK.RU, *supra* note 102.

¹⁰⁴ REVERA Law Firm Has Become an Official Partner of Pravo.Ru in Belarus, REVERA.BY (Dec. 22, 2020), https://revera.by/en/info-centr/730-revera-law-firm-has-become-an-official-partner-of-pravoru-in-belarus/.

¹⁰⁵ LEGAL MINER, https://www.legalminer.com/en/index (last visited Sept. 6, 2021).

do have some proprietary software entitled LAB Intelligence that is very similar in function and application to Premonition and Caselook. ¹⁰⁶ Furthermore, Legal Miner has partnered with LexisNexis, New York University School of Law, and other industry leaders who conduct business in China. ¹⁰⁷ At this time, there is scarcely any information on Legal Miner's business operations or where they plan to expand, but it is likely they will expand to the Russian Commonwealth of Independent States, and throughout Europe within the next few years.

As for Premonition, this U.S. based company has some of the best analytics in the world, and a hefty database of cases and documents going back decades throughout the U.S. legal system. They are expanding internationally into countries such as Canada, India, New Zealand, Ireland, Netherlands, United Kingdom, and Australia. This vast collection of data is well beyond anything LexisNexis, Westlaw, or Bloomberg law can muster and allows for unseen analytics, patterns, and the potential to predict outcomes of arbitration claims based upon prior public performance as an attorney, judge, or other published arbitration awards. Therefore,

¹⁰⁶ *Id*.

¹⁰⁷ *Id*.

¹⁰⁸ PREMONITION.AI, *supra* note 6.

¹⁰⁹ PREMONITION.AI, CANADA COURTS REPORT 2017 1–97 (2017), https://premonition.ai/reports/; Toby Unwin, *Premonition Analytics Adds India's High Court Records to World's Largest Litigation Database*, PREMONITION NEWS (Apr. 21, 2017) [hereinafter *Premonition Litigation Database*], https://www.newswire.com/news/premonition-analytics-adds-indias-high-court-records-to-worlds-largest-19207469; PREMONITION.AI, UK HIGH COURTS REPORT 2018 1–77 (2018), https://premonition.ai/reports/; PREMONITION COURT DATA, *supra* note 80, at 6; PREMONITION.AI, AUSTRALIA COURTS REPORT 2017 1–151 (2017), https://premonition.ai/reports/.

¹¹⁰ Toby Unwin, *An Unfair Advantage? Big Data Yields Surprising Results in Litigation*, PREMONITION NEWS (Oct. 26, 2014), https://test.premonition.ai/an-unfair-advantage-big-data-yields-surprising-results-in-litigation/; PREMONITION COURT DATA, *supra* note 80, at 1.

Premonition, Caselook, and other analytics companies are doing what was thought as impossible: providing analytics on arbitrators through indirect measurements.¹¹¹

Overall, international lit-jud-arb analytics will be an ever-expanding field where different approaches, datasets, and other AI programs are implemented, sabotaged, and fought over in the near future, but the promise of analytics outweighs its drawbacks and issues.

IV. LITIGATION AND JUDICIAL ANALYTICS TRANSLATED TO ARBITRAL ANALYTICS

The recent explosion in litigation and judicial analytics research, development, and implementation is just a new take on an old idea, but the field of arbitral analytics is almost devoid of research papers. There are many reasons for the lack of arbitration data, but one key reason is the confidentiality provisions surrounding many of the arbitration panels and awards since most disputes falling under an arbitration provision require confidentiality of the entire arbitration process. Additionally, most arbitrators see no reason, even when no confidentiality provision is in place, to publish their awards.

Given the lack of data on arbitrators, researchers have tried indirect methods of analyzing arbitrator data. The most common method employed by companies such as Bloomberg Law,

¹¹¹ The expansion of analytics into the arbitration field and internationally is a positive step forward; however, there is a dark side. For example, any government, with the right funding and contacts within another country, could use analytics to destroy or slowly subvert the rule of law in a targeted country over a few years. Thus, regulation of lit-jud-arb analytics is just a matter of time since this kind of power will likely cause at least one unprepared country to fall apart and even slide into civil war.

¹¹² Stewart & Stuhmcke, *supra* note 7, at 83.

¹¹³ Del. Coal. for Open Gov't, Inc. v. Strine, 733 F.3d 510, 525 (3d Cir. 2013) (listing confidentiality as a key reason why parties choose arbitration); Scherer, *supra* note 13, at 222–23 nn.92 (citing Paul B. Marrow, Mansi Karol, & Steven Kuyan, *Artificial Intelligence and Arbitration: The Computer as an Arbitrator--Are We There Yet?*, 74 DISP. RESOL. J. 35, 68 (2020)); Amy Schmitz, *Secrecy and Transparency in Dispute Resolution: Untangling the Privacy Paradox in Arbitration*, 54 U. KAN. L. REV. 1211, 1211–43 (2006).

¹¹⁴ Laurie Dore, *Public Courts Versus Private Justice: It's Time to Let Some Sun Shine in on Alternative Dispute Resolution*, 81 CHI.-KENT L. REV. 463, 482–93 (2006).

Lexis Nexis, Westlaw, Premonition, Gavelytics, Legal Miner, and Caselook involve analyzing old public litigation done by the arbitrator when working as an attorney, administrative law judge, judge, or through another public medium. This approach is most prominent when an arbitral institution, such as JAMS, publishes its entire arbitrator and mediator database online for anyone to review, so it is a simple task of searching the arbitrator's name and reviewing all relevant analytics on each service. The service is a simple task of searching the arbitrator's name and reviewing all relevant analytics on each service.

Another method of linking arbitrators is that of analyzing the social network of other arbitrators connected to your arbitrator. Langford found there was an inner circle of twenty-five arbitrators who dominated the arbitration community and were far more likely to be picked as an arbitrator compared to the outer circle vying for same role. Also, this inner circle had

¹¹⁵ PREMONITION.AI, *supra* note 6; LEXIS, *supra* note 5; WESTLAW, *supra* note 5; BLOOMBERG LAW, *supra* note 5; GAVELYTICS, *supra* note 6; LEGAL MINER, *supra* note 105; CASELOOK.RU, *supra* note 102. All these services allow for filtering based upon win rates, historical litigation records, litigation experience, dismissal rate, wording used, types of cases, clients, attorney/judicial relationships, and other specializations in law (ie. bankruptcy, wills and trusts, etc.). PREMONITION.AI, *supra*; LEXIS, *supra*; WESTLAW EDGE, *supra*; BLOOMBERG LAW, *supra*; GAVELYTICS, *supra*; LEGAL MINER, *supra*; CASELOOK.RU, *supra*; *see also* THOMPSON REUTERS, *Westlaw Edge*, Subpage *Litigation Analytics* (Sept. 23, 2020), https://legal.thomsonreuters.com/en/products/westlaw/edge/litigation-analytics; LEXISNEXIS, 2020 LEGAL ANALYTICS STUDY: BRINGING VALUE INTO FOCUS (2020), https://www.lexisnexis.com/en-us/products/lexis-analytics/2020-Legal-Analytics-Study.page?access=1-8468240001&treatcd=1-8440463367; BLOOMBERG LAW, *Litigation Analytics* (Sept. 23, 2020), https://pro.bloomberglaw.com/ai-analytics/.

¹¹⁶ JAMS, *Neutrals*, *All Neutrals* [hereinafter JAMS Neutrals], https://www.jamsadr.com/neutrals/ (last visited Jan. 8, 2021). Searching for an arbitrator or mediator on all available services can absorb large amounts of time and money, but this author has found attorneys, retired judges, and arbitrators lying in their resumes in these areas: active bar licenses, conflicts of interest, neutrality with attorneys, and other strange phenomena which have no explanation. It is advisable to pick two or three services with the largest document databases: Premonition, Gavelytics, and Bloomberg Law.

¹¹⁷ Langford, Behn, & Lie, *supra* note 57, at 2–13 (citing the international arbitrator community as prowestern, non-diverse, pro-investor, pro-investment, and well connected with each other).

¹¹⁸ *Id.* at 14–21.

substantial social network relationships with each other and the outer circle of the network. 119

The authors also found the ranking of the top twenty-five was influenced by the position on the tripartite arbitrator panel: presiding arbitrator, claimant arbitrator, or respondent arbitrator. 120

Given the blatant hierarchy presented by the analytics, the authors concluded there was asymmetric information flow from parties when picking an arbitrator and the lack of regulation over the arbitration community. 121 Since there is little to no arbitral regulation, power brokers and oligopolistic behaviour are likely occurring. 122 Thus, any critical arbitrator or attorney who is already part of the arbitrator's social network, would likely result in relegation to the outer social network circle; additionally, arbitrators tend to scratch each other's backs which can equate to unethical behavior. 123 Also, arbitrators and attorneys dislike disturbing their referral network even if there is questionable ethical conduct involved. 124 In conclusion, social network analytics provides a way to review the behaviour, ethical conduct, and other considerations of arbitrators that any judge would also be subject to prior to presiding over a case.

In addition to historical judicial and litigation analytics, one company, AIQ, is asking attorneys, clients, and other parties to input their arbitration outcomes and other information into

¹¹⁹ *Id*.

¹²⁰ *Id.* This same pattern was upheld for expert witnesses who also had an inner and outer circle. *Id.*

¹²¹ *Id.* at 26–28.

¹²² *Id*.

¹²³ *Id.* A key example would be an arbitrator and an attorney representing a party in one case switching roles in another unrelated ongoing case (eg. "double hatting"). *Id.* This could temp the arbitrator and attorney to reuse reasoned awards, motions, or favoritism from one case in another case they are in even though this kind of behavior is unethical since there is very little chance the parties would discover this arbitrator-attorney misconduct. *Id.*

¹²⁴ *Id.* There is sufficient evidence to find that "double hatting" of arbitrators is occurring, and they found arbitrators had acted as counsel in one case while simultaneously acting as an arbitrator in another case even though both cases involved the same legal issues. *Id.* at 28–34.

a detailed survey. 125 This would allow for outcome analysis, and reveal any details from answers the parties provide. 126 This is further analyzed with AI to discover patterns between the arbitrators and their public profiles in courts and other public filings. 127 Furthermore, AIQ is making deals with arbitral institutions to have their surveys sent to any party interacting with the cases, and in return, the institutions receive AI generated reports about arbitrators working under their roof. 128 This is similar to student reviews of professors in universities, but the stakes are higher since arbitrators, who might be removed for poor performance, might have their awards overturned by a court if the institution finds sufficient grounds to remove the arbitrator. However, this theory has yet to make it into any case.

V. USING MACHINE LEARNING TO EXPAND THE REACH AND VIABILITY OF LITIGATION, JUDICIAL, AND ARBITRAL ANALYTICS

In the world of litigation analytics, the main point of machine learning is to more accurately extract data from legal documents, and more importantly, filter this data into useful analytics. ¹²⁹ In many cases, the sheer volume of documents in the U.S. legal system makes any human review, page by page, next to impractical. ¹³⁰ In fact, the vast amounts of data make it impractical for any human to detect patterns affecting judicial or arbitral outcomes, so instead, AI methods are used to sift data into useful databases and to discover patterns where none were

¹²⁵ Nancy Welsh, *Dispute Resolution Neutrals' Ethical Obligation to Support Measured Transparency*, 71 OKLA. L. REV. 823, 859–60 (2019).

¹²⁶ *Id*.

¹²⁷ *Id*.

¹²⁸ *Id*.

¹²⁹ Chen, *supra* note 9, at 17–18; Aletras, Tsarapatsanis, Preotiuc-Pietro, & Lampos, *supra* note 20, at 1; Carlson, Livermore, & Rockmore, *supra* note 47.

¹³⁰ PREMONITION COURT DATA, *supra* note 80, at 4–5.

thought possible.¹³¹ Thus, since there are numerous methods of machine learning to process legal documents, it would be best to go through some of the published methods used to parse patterns from legal datasets.

One method of finding common "themes" between judges, arbitrators, and litigation in general is using probabilistic topic models from an unstructured collection of documents. ¹³² This approach uses Latent Dirichlet Allocation to find key words in a document via topics to associate other documents with similar topics that might be of some use to the reader. ¹³³ The program then uses probability based statistics to find words which likely match key words that are expected "topics" of the paper or judicial decision. ¹³⁴ David Blei uses the Yale Law Journal as a prime example of his program by extracting key words from the Journal, determining the probability of each key word, and suggesting, based upon these statistics, other law journal articles which might share the same author, legal discussion, or any other input the researcher

Carlson, Livermore, & Rockmore, *supra* note 47, at 1474–1510 (using AI to review all U.S. Supreme Court decisions between 1792 to 2008 for clerk writing patterns); Mulders, *supra* note 11, at 29 (using AI to review 15,217 cases without human review to find litigation analytic patterns); David Blei, *Probabilistic Topic Models*, 55 COMMC'N ACM 77, 77–80 (2012) (using LDA to process a substantial number of Yale Law Journal articles to find the topic of each article found within each publication). Further, Daniel Chen's paper recounts the digitization of 380,000 cases that were reviewed by AI to find patterns. Chen, *supra*. This amount of data would take a lifetime for one lawyer to review, and even then, the number of cases would be impossible for any person to remember. *Id.* Thus, the only way judicial/arbitral/litigation analytics is possible is using AI to process vast quantities of data in a short period of time.

¹³² Blei, *supra* note 131, at 77–78; Stenetorp, *supra* note 11; Dwivedi, *supra* note 11.

¹³³ Blei, *supra* note 131.

¹³⁴ *Id.* at 78–81.

may want.¹³⁵ Essentially, Westlaw uses a similar approach for their modern-day legal research database.¹³⁶ However, this method has advanced since this paper was published in 2012.

Another method is to analyze documents for key words which may be positive, negative, attacking, "giving face," firmness, and commands.¹³⁷ This approach basically assigns a value to these words and determines if the words used had a statistically measurable correlation to the time, length, and resolution of the case which did affect outcomes of up to 4.5 times when firm language was used in online dispute resolution.¹³⁸ Even though this data shows certain key words resulted in significant differences in dispute resolution outcomes, it does not take into account arbitrator or attorney drafted documents, so it may be useful if applied in the legal context at some later date.¹³⁹

Another older method is time series, and this method is well studied from the '90s onwards.¹⁴⁰ In this approach, the analyst can take large amounts of data and run frequency-domain methods or time-domain methods to find patterns in the wave format of the data.¹⁴¹ In essence, if you see the same pattern in the wave at several points, you can deduce the same effect is occurring for any number of reasons.¹⁴² This approach was used by Stacia to find there were

¹³⁵ *Id*.

¹³⁶ Vacek Motions and Orders, *supra* note 11, at 116–20; Vacek Case Outcome, *supra* note 11, at 45–53.

¹³⁷ Jeanne M. Brett, Mara Olekalns, Ray Friedman, Nathan Goates, Cameron Anderson, & Cara C. Lisco, *Sticks and Stones: Language, Face, and Online Dispute Resolution*, 50 ACAD. MGMT. J. 85–97 (2007).

¹³⁸ *Id*.

¹³⁹ *Id*.

¹⁴⁰ Haynie, *supra* note 11.

¹⁴¹ *Id*.

¹⁴² *Id*.

patterns in U.S. Supreme Court decisions.¹⁴³ Time series is a large and complex field that could have several dozen lit-jud-arb analytics papers on its own, so this is a very brief look at this approach.

A more recent method called NLP, which is a collection of different AI programs and methods to detect and understand language within a document, has shown great promise as a way to detect, determine, and predict the topic of the document being reviewed by the AI program. In Octavia-Maria Sulea's paper, the new SVM program outperformed an older NLP method from 2017 by up to 10% in the 87% to 98.6% accuracy range. Thus, it demonstrates the ability of AI to do the job that associate attorneys, paralegals, and other legal scholars did by hand no less than ten years ago. Another decision-tree based NLP from the Russian Federation also shows statistical analysis and further research into ML for legal claims in Russian courts and arbitrations that can result in better decision making by the Russian Federal Government and their respective oblasts when new regulations are contemplated. Thus, NLP and SVM would be ideal for arbitral analytics on large datasets.

Furthermore, Chen's work demonstrates that using ML and AI, in general, can generate highly accurate predictions on judges of around 82–88% depending upon the method applied to

¹⁴³ *Id*.

¹⁴⁴ Octavia-Maria Sulea, Marcos Zampieri, Shervin Malmasi, Mihaela Vela, Liviu P. Dinu, & Josef van Genabith, *Exploring the Use of Text Classification in the Legal Domain*, AUTOMATED SEMANTIC ANALYSIS INFO. LEGAL TEXT (ASAIL) 1, 1–5 (2017).

¹⁴⁵ *Id*.

¹⁴⁶ Connell, *supra* note 9; Koebler, *supra* note 13.

¹⁴⁷ Metsker, Trofimov, Petrov, & Nikolay, *supra* note 20, at 265–72.

the dataset.¹⁴⁸ This kind of analytics of judges, internationally and in the U.S., was further supported by Aletras' research which could predict the result of the European Court of Human Rights with a 79% accuracy based solely on textual analysis.¹⁴⁹ Indeed, there are numerous papers in the last five years, cited throughout this paper, showing the same results as the papers mentioned in this section.¹⁵⁰

Thus, since judicial analytics can now be deemed as a real science with significant weight behind its use in legal claims throughout the world, it is safe to say that the same can be said with arbitration if identical approaches are used to analyze reasoned arbitration awards. However, the datasets available, as previously discussed, will not reflect all available awards written by an arbitrator; but based upon historical analysis alone, they can be immensely valuable when picking and approaching arbitrators.

VI. BACKGROUND ON FINRA ARBITRATION ANALYSIS

FINRA provides arbitration services, with Security and Exchange Commission (SEC) oversight, to investor and broker disputes. Whenever an arbitration claim is made through FINRA, any written award must be published on the FINRA website to the general public. Since these awards are required to be public; detail the parties; identify the arbitrator or

¹⁴⁸ Chen, *supra* note 9, at 15–40.

¹⁴⁹ Aletras, Tsarapatsanis, Preotiuc-Pietro, & Lampos, *supra* note 20, at 1, 12–16.

¹⁵⁰ See also Deeks, supra note 4, at 577–653.

¹⁵¹ FINRA, *What We Do*, https://www.finra.org/about/what-we-do (last visited Jan. 8, 2021); Arbitration Agreements, 82 Fed. Reg. 33210, 33210–348 (July 19, 2017).

¹⁵² FINRA, RULE 12904(h) (2018).

arbitrators; provide a reasoned award; and list the granted amounts and the denied claims, this extensive database is one of many ideal locations to apply judicial analytics to arbitrations.¹⁵³

From this vast repository, I was able, with the aid of Chad Davies, to extract, combine, and analyze 2,449 arbitration awards which accounts for roughly 70% of all available FINRA published awards.¹⁵⁴ This large amount of data created a vast database of approximately 649,751 words written within the sample award database and 2,503 granted awards of \$1.00 or more to the claimants to the dispute.¹⁵⁵ Additionally, there were 1,120 denied claims in this database as well.¹⁵⁶ From this data, we were able to apply two different analytical approaches, as detailed in the following sections, to this data, but this is by no means the only analytics which could be applied. Indeed, this is only the starting point, and this research could be taken well beyond this with more time, resources, and different ML programs applied.

VII. BENFORD'S LAW ANALYSIS ON FINRA EXTRACTED DATA

When analyzing any kind of document which includes financial information or amounts, it is advisable to check if whether those numbers are skewed outside of a normal distribution.

Abnormal distribution would indicate bias, fraud, or another phenomenon which is potentially

¹⁵³ *Id.* at §12904(e); FINRA, *Arbitration Awards Online*, https://www.finra.org/arbitration-mediation/arbitration-awards (last visited Jan. 8, 2021).

¹⁵⁴ See Chad Davies & Benjamin Davies, FINRA DATA GROUP WORD COUNT, *Word Count Data (Benjamin Davies, 2021) [hereinafter WORD COUNT DATA], https://ldrv.ms/u/s!AisD4iL98oQKhscZ-UTLa9I2GKL4Kw?e=4DYYwG (a complete list of this data is available from Microsoft OneDrive). This database is by no means a population of all published FINRA arbitration awards, but it constitutes a reasonable sample size for the purposes of this paper. *Id*.

¹⁵⁵ *Id*.

¹⁵⁶ *Id*.

affecting the reported numbers in the documents, in which case further investigation would be warranted to check the data in question.¹⁵⁷

A common method is called Benford's Law. ¹⁵⁸ While Benford's Law cannot definitively prove or disprove fraud on its own, it acts as a heavily weighted factor when determining a dataset's bias . ¹⁵⁹

To begin, Benford's Law takes every reported number (e.g., \$4,576), extracts the first digit from the number (e.g., 4), and counts the number of times each number appears on the number line from one to nine. Once the count is finalized, the distribution is determined by dividing the count of a particular number (e.g., the number "4" which has a count of 207) by the total count of all the numbers combined, which is then multiplied by 100 to create a percentage. 161

To better explain the sample data analyzed in this paper, an example of the math used to calculate the percentage for the number "4" is below:

$$\left(\frac{x_c}{x_t}\right) * 100 = Percent Distribtuion of x_c$$

Where,

 x_c = the count of the particular number chosen

https://projecteuclid.org/download/pdfview_1/euclid.ps/1311860830.

¹⁵⁷ Collins, *supra* note 55; Banu Demir & Beata Javorcik, *Using Benford's Law to Detect Tax Fraud in International Trade*, VOXEU CEPR (Sept. 17, 2018), https://voxeu.org/article/using-benford-s-law-detect-tax-fraud-international-trade; Arno Berger & Theodore Hill, *A Basic Theory of Benford's Law*, 8 PROBABILITY SURVEYS 1, 1–126 (2011),

¹⁵⁸ See Collins, supra note 55; Demir & Javorcik, supra note 157; Berger & Hill, supra note 157.

¹⁵⁹ See Demir & Javorcik, supra note 157; Collins, supra note 55.

¹⁶⁰ See Berger & Hill, supra note 157, at 2–59; Demir & Javorcik, supra note 56; Collins, supra note 55.

¹⁶¹ See Berger & Hill, supra note 157, at 2–59; Demir & Javorcik, supra note 56; Collins, supra note 55.

 $x_t =$ the count of each number summed into a total

Step 1:
$$\left(\frac{x_4}{x_t}\right)$$
 * 100 = Percent Distribution of x_4

Step 2:
$$\left(\frac{207}{2503}\right) * 100 = Percent Distribution of $x_4$$$

Step 3:
$$(.0827) * 100 = Percent Distribution of x_4$$

Step 4: Percent Distribtuion of $x_4 = 8.27\%$

Thus, when applied to the arbitration awards for amounts granted, we can check-whether the data follows Benford's law. Thus, the ML program scraped any dollar amount, treated it as an award, extracted the first digit from the dollar amount, and counted it in the number line. After reviewing the entire data set, the program found a total of 2,503 granted financial awards with the respective number line counts of (1) 850, (2) 415, (3) 342, (4) 207, (5) 212, (6) 162, (7) 152, (8) 102, and (9) 61. From these sample data's calculated percentages, an analyst can compare the actual percentages to the ideal Benford curve percentages which are calculated from the equation $10^2 * \log(1 + d^{-1})$. This is reflected in a table from the Excel spreadsheet entitled "FINRA Data Benford Curve" and Figure 1 below.

¹⁶² See Chad Davies & Benjamin Davies, Raw Data, FINRA DATA BENFORD CURVE, (2021) [hereinafter BENFORD CURVE], https://ldrv.ms/u/s!AisD4iL98oQKhscZ-UTLa9I2GKL4Kw?e=4DYYwG (a complete list of this data is available from Microsoft OneDrive).

¹⁶³ See Berger & Hill, supra note 157, at 18 (discussing how the Fibonacci numbers conform to the first digit law found in Benford's law).

¹⁶⁴ See BENFORD CURVE, supra note 162.

Figure 1:

Benford's Law Number Line Count								
Number	Count	Data %	Ideal Benford %	% Difference				
1	850	33.96%	30.10%	3.86%				
2	415	16.58%	17.60%	-1.02%				
3	342	13.66%	12.50%	1.16%				
4	207	8.27%	9.70%	-1.43%				
5	212	8.47%	7.90%	0.57%				
6	162	6.47%	6.70%	-0.23%				
7	152	6.07%	5.80%	0.27%				
8	102	4.08%	5.10%	-1.02%				
9	61	2.44%	4.60%	-2.16%				
Sum Total	2,503	100.00%	100.00%					

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Within Figure 1, the percentages calculated from the count in the column entitled "Data %" indicate that the data from the FINRA arbitration awards follows Benford's Law—the column entitled "Ideal Benford %"—consistently, except for two numbers: 1 and 9.166 These two numbers, in Figure 1, were both slightly outside of a normal distribution under Benford's Law, with "1" being 3.86% above the normal 30.10% and "9" being -2.16% below the normal 4.60%.167 This percentage difference is more pronounced under the Excel spreadsheet tab entitled "Combined Benford % Chart," and incorporated as Figure 2 below as a histogram graph.168

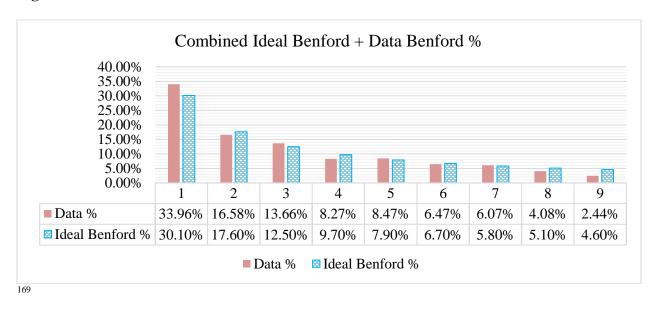
¹⁶⁵ BENFORD CURVE, *supra* note 162.

¹⁶⁶ See Benford Curve, supra note 162.

¹⁶⁷ See BENFORD CURVE, supra note 162.

¹⁶⁸ See BENFORD CURVE, supra note 162.

Figure 2:



Since the granted dollar amount awards follow Benford's Law so closely, it is my belief that an unknown phenomenon might be causing the disparity with the two outlier numbers.

Thus, it is likely a multitude of issues: the nominal \$1.00 award, the cognitive bias of FINRA arbitrators to round up awards starting with a "9" to the closest "1" (e.g. \$934,000 to \$1,000,000), sample size, and typos likely play a role in these results. However, until further detailed research can be completed, these ideas are just theories lacking any supporting data. Furthermore, I speculate confirming and vacating judicial awards may alter the data away from the ideal Benford Curve percentages, but this is ripe for another paper specifically dealing with this subject. Therefore, for the purposes of this paper, it is highly likely the arbitrators are, on average, granting dollar amount claims in a fair manner. However, the overall Benford Curve does not account for arbitrators or arbitration panels who might fall outside of the Benford Curve, but there is insufficient data to properly address this issue.

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¹⁶⁹ BENFORD CURVE, *supra* note 162, at Combined Benford % Chart.

VIII. MACHINE LEARNING WORD COUNT ANALYTICS FOR FINRA ARBITRATIONS

The second ML arbitral analytics approach was derived from a judicial analytics paper following a similar path to our own program.¹⁷⁰ In the team paper authored by Nikolaos Aletras, the team analyzed all the words in 584 cases before the European Court of Human Rights.¹⁷¹ The paper references a predictive accuracy of 79%, which will be assumed to be similar to our own.¹⁷² The vast size of our data set made building a predictive accuracy ML model complex, and beyond the scope of this paper since a later paper would better fit, discuss, and build out a ML prediction model.¹⁷³

In this paper, we scraped the FINRA arbitration award database for any published awards from 2011 to 2020. Next, we processed these documents via ML programs from their images, pdfs, and other file types into text files which were loaded into an Oracle database. From there, we used several different ML programs to process the awards for their word counts and their granted and denied counts associated with those words in each award. Finally, a complete list of words with the associated granted and denied rates was created.

To make the program efficient and to streamline basic analytics from a new ML approach never tried, we kept the criteria simple. First, a granted award was always an amount granted to

¹⁷⁰ See Aletras, Tsarapatsanis, Preotiuc-Pietro, & Lampos, supra note 20, at 1, 12–16.

¹⁷¹ *Id.* at 8.

¹⁷² *Id.* at 1–2. However, without further investigation in a subsequent paper, this assumption should be used as a rule of thumb since our own AI program would likely produce a similar accuracy prediction.

¹⁷³ The sheer volume of data made the coding section of this paper too complex and difficult to build out properly within the short timeframe required for this paper. Thus, given the complex nature of FINRA arbitration awards, we will focus on ML use in scanning, analyzing, and determining which words had the highest grant and deny rates within the sample.

¹⁷⁴ Essentially, if the word "trustee" was found in the document, the program would mark this word, apply textual analysis, and determine how many granted awards and denied awards were included.

the claimant (e.g., \$9,000.00), so it would count once towards all the words scraped from that particular award. Therefore, if there were seven different claims granted within the same arbitrator award, each word would have their granted count increased by seven. The same approach was used for denied claims, but the program was designed to detect and discard blanket denials of claims that were not part of the reasoned award. For example, many arbitrators would only address the key claims in the arbitration and would either use a list or a general "all other claims by the claimants are hereby denied" phrase. Additionally, the ML programs ignored all arbitration awards or denials where expungement was attached since this kind of award can be complicated for ML programs to decipher without significant coding beyond the purview of this paper. Also, there were typos within the dataset, but these were accounted for, and did count as a separate word since typos might show the arbitration panel was tired, rushed, or any other state which might cause a typo to occur. This might be a potential analytic type since it might show an arbitrator specific issue which could affect their reasoning and mental capacity if it can be proven to occur over several of their arbitrations.

Turning to the data, there were 4,899 unique words found through the entire database with the top twenty highest counted words listed in Figure 3 below.¹⁷⁵

¹⁷⁵ WORD COUNT DATA, *supra* note 154.

Figure 3:

Top 20 Counted Words								
Word	Count	Denied Grant		Grant/Denied	%	%	Multiples	
		Count	Count	Sum	Granted	Denied	Multiples	
claimant	3,225	4,782	9,530	14,312	66.59%	33.41%	2.0	
statement	3,092	4,446	10,606	15,052	70.46%	29.54%	2.4	
expungement	2,878	4,156	8,559	12,715	67.31%	32.69%	2.1	
claimants	2,639	3,671	11,802	15,473	76.27%	23.73%	3.2	
claim	2,618	3,814	9,304	13,118	70.93%	29.07%	2.4	
respondent	2,301	3,301	6,581	9,882	66.60%	33.40%	2.0	
arbitrator	2,210	3,095	6,065	9,160	66.21%	33.79%	2.0	
hearing	2,057	2,933	6,574	9,507	69.15%	30.85%	2.2	
other	1,939	2,741	6,465	9,206	70.23%	29.77%	2.4	
requested	1,833	2,741	6,384	9,125	69.96%	30.04%	2.3	
award	1,609	2,291	5,510	7,801	70.63%	29.37%	2.4	
finra	1,548	2,286	5,565	7,851	70.88%	29.12%	2.4	
arbitration	1,532	2,138	5,070	7,208	70.34%	29.66%	2.4	
answer	1,433	2,107	4,852	6,959	69.72%	30.28%	2.3	
filed	1,410	2,020	4,797	6,817	70.37%	29.63%	2.4	
damages	1,380	2,083	4,729	6,812	69.42%	30.58%	2.3	
request	1,358	1,942	4,237	6,179	68.57%	31.43%	2.2	
respondents	1,264	1,911	5,086	6,997	72.69%	27.31%	2.7	
panel	1,250	1,712	5,277	6,989	75.50%	24.50%	3.1	
parties	1,212	1,713	3,754	5,467	68.67%	31.33%	2.2	
176	•	•						

In Figure 3, the "Word" column shows the word, while columns "Count, Denied Count, and Grant Count" show how many times the word was counted and the corresponding number of times the word was associated with the denied or granted awards. The next three columns "Granted %, Denied %, and Multiples" indicate the percentages of the total number of times a word was linked to a grant and denied; the multiple calculates the number of times, the larger of the "Grant Count" or "Denied Count," was when the smaller number was divided into the larger number. The "Multiple" column is the most useful and shows whether a word has an extremely high denied or grant rate compared to other words. In Figure 3, the granted and denied

¹⁷⁶ *Id.* at Top 20 Used Words.

percentages fell around 70% which is nothing special, and the multiples were between 2.0 and 3.1 which also shows nothing of note.

In Figure 4 and 5 below, the top twenty words with high granted and denied multiples are listed in ascending order.¹⁷⁷

Figure 4:

Top 20 Granted Words with Multiples									
Word	Count	Denied Count	Grant Count	Grant/Denied Sum	% Granted	% Denied	Multiples		
remaining	48	57	985	1042	94.53%	5.47%	17.3		
trust	53	71	768	839	91.54%	8.46%	10.8		
first	77	89	831	920	90.33%	9.67%	9.3		
became	33	45	330	375	88.00%	12.00%	7.3		
david	46	68	458	526	87.07%	12.93%	6.7		
michael	41	64	427	491	86.97%	13.03%	6.7		
hereinafter	36	56	328	384	85.42%	14.58%	5.9		
additionally	33	38	213	251	84.86%	15.14%	5.6		
referred	40	64	347	411	84.43%	15.57%	5.4		
payment	89	108	557	665	83.76%	16.24%	5.2		
james	90	147	758	905	83.76%	16.24%	5.2		
limited	51	78	402	480	83.75%	16.25%	5.2		
applicable	47	62	319	381	83.73%	16.27%	5.1		
davidson	35	70	350	420	83.33%	16.67%	5.0		
exhibit	107	133	662	795	83.27%	16.73%	5.0		
collectively	46	70	341	411	82.97%	17.03%	4.9		
fraudulent	48	69	333	402	82.84%	17.16%	4.8		
second	127	166	801	967	82.83%	17.17%	4.8		
settled	89	128	611	739	82.68%	17.32%	4.8		
unnamed	31	40	187	227	82.38%	17.62%	4.7		

¹⁷⁷ *Id.* at Top 20 Granted Multiples.

¹⁷⁸ *Id.* at Top 20 Granted Multiples.

Figure 5:

Word Count Denied Count Grant Jount Sum Granted Granted Denied Multiples citi group 33 76 67 143 46.85% 53.15% 1.13 expunged 45 66 82 148 55.41% 44.59% 0.80 involved 38 65 83 148 56.08% 43.92% 0.78 occurrences 34 53 70 123 56.91% 43.09% 0.76 numbers 218 417 561 978 57.36% 42.64% 0.74 wrongdoing 35 64 87 151 57.62% 42.38% 0.74 case-in-chief 49 91 124 215 57.67% 42.33% 0.73 objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 </th <th colspan="9">Top 20 Denied Words with Multiples</th>	Top 20 Denied Words with Multiples								
citi group 33 76 67 143 46.85% 53.15% 1.13 expunged 45 66 82 148 55.41% 44.59% 0.80 involved 38 65 83 148 56.08% 43.92% 0.78 occurrences 34 53 70 123 56.91% 43.09% 0.76 numbers 218 417 561 978 57.36% 42.64% 0.74 wrongdoing 35 64 87 151 57.62% 42.38% 0.74 case-in-chief 49 91 124 215 57.67% 42.33% 0.73 objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 <	Word	Count	Denied Grant		Grant/Denied	%	%	Multiples	
expunged 45 66 82 148 55.41% 44.59% 0.80 involved 38 65 83 148 56.08% 43.92% 0.78 occurrences 34 53 70 123 56.91% 43.09% 0.76 numbers 218 417 561 978 57.36% 42.64% 0.74 wrongdoing 35 64 87 151 57.62% 42.38% 0.74 case-in-chief 49 91 124 215 57.67% 42.33% 0.73 objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.67 erroneous 50 <			Count	Count	Sum	Granted	Denied	Multiples	
involved 38 65 83 148 56.08% 43.92% 0.78 occurrences 34 53 70 123 56.91% 43.09% 0.76 numbers 218 417 561 978 57.36% 42.64% 0.74 wrongdoing 35 64 87 151 57.62% 42.38% 0.74 case-in-chief 49 91 124 215 57.67% 42.33% 0.73 objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50	citi group	33	76	67	143	46.85%	53.15%	1.13	
occurrences 34 53 70 123 56.91% 43.09% 0.76 numbers 218 417 561 978 57.36% 42.64% 0.74 wrongdoing 35 64 87 151 57.62% 42.38% 0.74 case-in-chief 49 91 124 215 57.67% 42.33% 0.73 objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31	expunged	45	66	82	148	55.41%	44.59%	0.80	
numbers 218 417 561 978 57.36% 42.64% 0.74 wrongdoing 35 64 87 151 57.62% 42.38% 0.74 case-in-chief 49 91 124 215 57.67% 42.33% 0.73 objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.49% 0.65 litigation 56	involved	38	65	83	148	56.08%	43.92%	0.78	
wrongdoing 35 64 87 151 57.62% 42.38% 0.74 case-in-chief 49 91 124 215 57.67% 42.33% 0.73 objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56	occurrences	34	53	70	123	56.91%	43.09%	0.76	
case-in-chief 49 91 124 215 57.67% 42.33% 0.73 objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226	numbers	218	417	561	978	57.36%	42.64%	0.74	
objected 47 97 133 230 57.83% 42.17% 0.73 responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	wrongdoing	35	64	87	151	57.62%	42.38%	0.74	
responses 32 43 60 103 58.25% 41.75% 0.72 false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	case-in-chief	49	91	124	215	57.67%	42.33%	0.73	
false 72 115 165 280 58.93% 41.07% 0.70 deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	objected	47	97	133	230	57.83%	42.17%	0.73	
deliberation 52 89 128 217 58.99% 41.01% 0.70 financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	responses	32	43	60	103	58.25%	41.75%	0.72	
financial 117 194 289 483 59.83% 40.17% 0.67 erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	false	72	115	165	280	58.93%	41.07%	0.70	
erroneous 50 78 117 195 60.00% 40.00% 0.67 disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	deliberation	52	89	128	217	58.99%	41.01%	0.70	
disgorgement 31 44 67 111 60.36% 39.64% 0.66 finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	financial	117	194	289	483	59.83%	40.17%	0.67	
finding 40 62 95 157 60.51% 39.49% 0.65 litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	erroneous	50	78	117	195	60.00%	40.00%	0.67	
litigation 56 82 127 209 60.77% 39.23% 0.65 sanctions 226 316 490 806 60.79% 39.21% 0.64	disgorgement	31	44	67	111	60.36%	39.64%	0.66	
sanctions 226 316 490 806 60.79% 39.21% 0.64	finding	40	62	95	157	60.51%	39.49%	0.65	
	litigation	56	82	127	209	60.77%	39.23%	0.65	
ioint 73 112 174 286 60.84% 39.16% 0.64	sanctions	226	316	490	806	60.79%	39.21%	0.64	
John 75 112 171 200 00.0170 39.1070 0.01	joint	73	112	174	286	60.84%	39.16%	0.64	
motions 45 67 105 172 61.05% 38.95% 0.64	motions	45	67	105	172	61.05%	38.95%	0.64	
factually 48 75 118 193 61.14% 38.86% 0.64	factually	48	75	118	193	61.14%	38.86%	0.64	

The same details and explanations from Figure 3 apply to Figures 4 and 5. Some of the many inferences and findings from this data show granted rates are substantially higher than denied rates. In fact, any multiple over five for a granted rate in Figure 4 is unusually high.

Furthermore, words from the granted list indicate trust accounts, first claims or investments, remaining amounts in an account, hereinafter, additionally, exhibits to a claim, or certain individuals were far more likely to have arbitrator scrutiny and likely, higher grant rates given some reasoning (ie. fiduciary duty levels for trust accounts). There is an almost limitless number of inferences one can make from these data, but without further research and ML

¹⁷⁹ *Id.* at Top 20 Denied Multiples.

application, it is difficult to find patterns or phenomena that defy logical explanation. One example is the names of individuals associated with high multiples: this could be one person committing a Ponzi scheme against several individuals, the "Karen" effect applied to another name, ¹⁸⁰ or some other explanation that requires further investigation.

Basically, an attorney could use this word pattern to write arbitration claims, briefs, and other filings to the arbitration panel to increase the odds they receive even a nominal amount for clients. Furthermore, the "Denied" list shows words the claimant's attorney should avoid, whereas respondent's attorney should try to use these words to increase the likelihood the arbitrator will deny some or all claims.¹⁸¹

Because researchers found multiples match similar patterns in the European Court of Human Rights, one may find some judicial analytics could equally apply as arbitral analytics. As always, this is a preliminary step, and there is far more research, analysis, and peer review to be done before one may definitively prove this claim. However, these preliminary results show serious promise that one may use judicial analytics on arbitrators who have historical litigation or judicial analytics.

¹⁸⁰ In 2021, the name Karen holds a negative connotation and bias. *See, e.g.*, Petula Dvorak, *It's Great to Have a Name for 'Karen' Behavior. Sorry It's Yours, Karen.*, WASH. POST (Dec. 9, 2021), https://www.washingtonpost.com/dc-md-va/2021/12/09/karen-meme-name-white-women/ (describing the origin of this phenomenon on social media). So, the "Karen" effect could apply to any kind of bias a name holds. Thus, in future research, the names of the parties should be considered when determining if an award was granted or denied as there might be a correlation or causation associated with a party's name.

¹⁸¹ Attorneys will likely need to consider multiples, similar to those in this paper, to ensure they are advocating for their client's best interest and to show they did their due diligence on the arbitrator and on the claims in the case.

¹⁸² See Aletras, Tsarapatsanis, Preotiuc-Pietro, & Lampos, *supra* note 20, at 13–15 (displaying use of multiples in a judicial analytics context).

IX. CONCLUSION

In conclusion, litigation, judicial, and arbitral analytics are a relatively new take on a century-old idea. Analytics promises to fundamentally change the legal profession and how one analyzes, approaches, and represents claims before a court or arbitration panel, as well as the public's perception of a fair hearing under the right to due process of law.

Additionally, several private and governmental actors are actively researching, building, and applying analytics to negotiations, court cases, and arbitration claims. However, governments and bar associations throughout the world must address numerous known and unknown ethical issues before abuse becomes a major problem for the rule of law in their respective jurisdictions.

Also, all three types of analytics—descriptive, predictive, and prescriptive—suffer from extraction issues, given the complex and the fragmented nature of court systems that is especially acute among U.S. courts.¹⁸⁴ Additionally, there are ethical concerns when poor-quality analytics are used to eliminate arbitrators or judges from this fragmented data based on conflicts of interest. However, ML and AI show serious promise and have proven to overcome these issues when coded correctly and applied in a clear and easy manner to follow for attorneys, judges, and arbitrators who may lack the scientific and mathematical understanding for such advanced analytics in their respective cases.¹⁸⁵

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¹⁸³ See, e.g., PREMONITION.AI, supra note 6; GAVELYTICS, supra note 6; CASELOOK.RU, supra note 102; Alschner, supra note 4; Deeks, supra note 4, at 583–84, 594–95, 625–33 nn.273–74 (citing CHARLOTIN STYLOMETRIC ANALYSIS, supra note 93); WHALEN, supra note 94; Weber, supra note 3.

¹⁸⁴ See Borden & Baron, supra note 13, at 23 (defining the three types of analytics).

¹⁸⁵ See, e.g., Chen, supra note 9, at 17–18; Aletras, Tsarapatsanis, Preotiuc-Pietro, & Lampos, supra note 20, at 1; Carlson, Livermore, & Rockmore, supra note 47.

However, I believe analytics with ML and AI display great promise to not only protect the rule of law in the U.S. and around the world, but to increase the fairness judges, and increasingly arbitrators, are perceived and proven to have when overseeing cases that may affect society at large or substantial parts of a country's or region's economic activity. Therefore, I hope this paper serves to begin discussions on how governments, courts, bar associations, and the public should approach, review, and potentially regulate analytics.