

PREDICTING PRECEDENT: A PSYCHOLINGUISTIC ARTIFICIAL INTELLIGENCE IN THE SUPREME COURT

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Since the proliferation of analytic methodologies and ‘big data’ in the 1980s, there have been multiple studies claiming to offer consistent predictions for Supreme Court behavior. Political scientists focus on analyzing the ideology of judges, with prediction accuracy as high as 70%. Institutionalists, such as Kaufmann (2019), seek to make predictions on verdicts based on a thorough, qualitative analysis of rules and structures, with predictive accuracy as high as 75%. We argue that a psycholinguistic model utilizing machine learning (SCOTUS_AI) can best predict Court outcomes. Extracting sentiment features from parsed briefs through the Linguistic Inquiry and Word Count (LIWC), our results indicate SCOTUS_AI (AUC = .8087; Top K=.9144) outcompetes traditional analysis in both class-controlled accuracy and range of possible, specific outcomes. Moreover, unlike traditional models, SCOTUS_AI can also predict the procedural outcome of the case as one-hot encoded by remand (AUC=.76). Our findings support a psycholinguistic paradigm of case analysis, suggesting that the framing of arguments is a relatively strong predictor of case results. Finally, we cast predictions for the Supreme Court docket, demonstrating that SCOTUS_AI can be practically deployed in the field for individual cases.

Key words: Supreme Court, artificial intelligence, psycholinguistic, institutionalism

CONTENTS

I.	Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court.	220
II.	Literature Review	223
III.	Institutionalist Models	223
IV.	Psycholinguistic Models	225
V.	Predictive Algorithms in Court Behavior	233
VI.	Methodology	240
VII.	Variables	242
VIII.	Data Collection.....	244
IX.	Analysis	244
X.	Results.....	249
XI.	Model Performance	250
XII.	Case Example Predictions.....	252
XIII.	Discussion	256
XIV.	Limitations and Future Research.....	263
XV.	Conclusion	269

I. Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

“The object of our study, then, is prediction, the prediction of the incidence of the public force through the instrumentality of the courts.”¹

Since the proliferation of analytic methodologies and ‘big data’ in the 1980s,² multiple studies have been developed attempting to comprehensively explain Supreme Court behavior.³ These studies have ranged from correlating ideological measurements and voting patterns to concrete assertions by Supreme Court Justices that outcomes are almost wholly dependent on the legal context—that is, “the ordinary sense of words, history, tradition, precedents, purposes... and consequences related to those purposes.”⁴ Furthermore, the increasingly large social impact of Supreme Court cases has led scholars, policymakers, and political pundits alike to invest in predicting case outcomes,⁵ even so that entire

¹ Oliver Wendell Holmes, *The Path of the Law*, 10 HARV. L. REV., 4751 (1897).

² See generally Kate Crawford, Kate Miltner & Mary Gray, *Critiquing Big Data: Politics, Ethics, Epistemology*, 8 INTL. J. OF COMM. 1663 (2014).

³ See Jeffrey Allan Segal & Harold J. Spaeth, *The Supreme Court and the Attitudinal Model*, 88 AM. POL. SCI. REV. 485 (1993) (for an early, systemic method of quantitatively predicting Supreme Court cases); See, e.g., Jeffrey A. Segal, *Predicting Supreme Court cases Probabilistically: The Search and Seizure cases, 1962-1981*, 78 AM. POL. SCI. REV. 891 (1984) (in analyzing search and seizure cases probabilistically between 1962-1981); See generally: Margaret E. Roberts et al., NAVIGATING THE LOCAL MODES OF BIG DATA, in COMPUTATIONAL SOCIAL SCIENCE: DISCOVERY AND PREDICTION 51–52 (R. Michael Alvarez ed., 2016) (explaining that the explosion of available data “opens new possibilities for studies of all aspects of political life from public opinion...”); Thomas G. Hansford & James F. Spriggs, MEASURING THE INTERPRETATION OF PRECEDENT, in THE POLITICS OF PRECEDENT ON THE U.S. SUPREME COURT 43–54 (2018).

⁴ STEPHEN BREYER, THE AUTHORITY OF THE COURT AND THE PERIL OF POLITICS 64 (2021); See Jeffrey A. Segal & Albert D. Cover, *Ideological values and the votes of U.S. Supreme Court Justices*, 83 AM. POL. SCI. REV. 557, 557–565 (1989); See, e.g., Charles M. Cameron & Jee-Kwang Park, *How will they vote? Predicting the Future Behavior of Supreme Court nominees, 1937-2006*, 6 J. EMPIRICAL L. STUDIES, 485 (2009) (for an analysis on predicting voting behavior based on a nominee’s political ideology).

⁵ See Brandon L. Bartels & Christopher D. Johnston, *On the Ideological Foundations of Supreme Court Legitimacy in the American Public*, 57 AM. J. OF POL. SCI. 184 (2012) (in suggesting that the public’s perception of court legitimacy has an ideological, policy function: “As the results of this study make clear, the Court’s legitimacy in the mass public is significantly influenced by individuals’ perceived ideological disagreement with the Court’s policymaking.”); See e.g., Christopher Walker, *Attacking Auer and Chevron Deference: A Literature Review Symposium: Challenging Administrative Power*, 16 THE GEO. J. OF L. AND PUB. POL’Y 103, 104 (2018) (explaining the emphasis placed on administrative doctrines: “[i]n recent years, we have seen a growing call from the federal bench, on the Hill, and within the legal academy to rethink administrative law’s deference doctrines to federal agency interpretations of law...”); See also, e.g., Emily Kazyak & Mathew Stange, *Backlash or a Positive Response? Public Opinion of LGB Issues After Obergefell v. Hodges*, 65 J. OF HOMOSEXUALITY 2028 (2018).

betting markets have emerged solely focused on predicting court outcomes.⁶ As some commentators have noted, the 2022 term is likely to be one of the most impactful in recent history, with an overwhelmingly conservative court granting certiorari on a number of issues ranging from the constitutionality of affirmative action, religious freedom, free speech, the right to bear arms, due process, equal protection, and administrative deference.⁷ Criticism during this term has also been emotionally explosive, with some arguing the Court has been “unhinged” and “partisan.”⁸ These criticisms are not particularly new. Almost immediately before Thurgood Marshall resigned, he wrote a scathing dissent in *Payne v. Tennessee*: “Neither the law nor the facts ... underwent any change in the last four years. Only the personnel of this court did.”⁹ Scalia, sitting on the opposite ideological side as Marshall, would later similarly write in his dissent in *Obergefell v. Hodges* that the Supreme Court had “descended from the disciplined legal reasoning of John Marshall and Joseph Story to the mystical aphorisms of the fortune cookie.”¹⁰ To Marshall and Scalia, it was the individual preferences of justices sitting on the court, not the framing of arguments, that determined how the Court ruled.

⁶ See Miriam Cherry & Robert Rogers, *Tiresias and the Justices: Using Information Markets to Predict Supreme Court Decisions*, 100 NW. U. L. REV. 1141 (2006); See, e.g., *Will Supreme Court rule Against Federal Sports Betting Ban?*, PREDICTIT (2018), <https://www.predictit.org/markets/detail/3923/Will-Supreme-Court-rule-against-federal-sports-betting-ban> (last visited Apr 11, 2022) (in offering a betting market on the question of “[shall] the US Supreme Court rule in the case of *Christie v. National Collegiate Athletic Association* and/or *New Jersey Thoroughbred Horsemen’s Association, Inc. v. National Collegiate Athletic Association*, that a federal statute that prohibits adjustment or repeal of state-law prohibitions on private conduct does impermissibly commandeer the regulatory power of States in contravention of *New York v. United States*, 505 U. S. 144 (1992), and/or *Printz v. United States*, 521[?]”) [<https://perma.cc/AP8M-JB7H>].

⁷ See, e.g., Tanner Stening, *Abortion, Guns, Religion: Here are the Major US Supreme Court cases for 2022*, NORTHEASTERN GLOBAL NEWS (Jan. 18, 2022), <https://news.northeastern.edu/2022/01/18/major-supreme-court-cases-2022/> [<https://perma.cc/KG5C-DRC2>]; See also, e.g., Alexander Philips, *5 Supreme Court Cases to Watch in the 2021-22 Term*, THE HERITAGE FOUNDATION (Sept. 28, 2021), <https://www.heritage.org/courts/commentary/5-supreme-court-cases-watch-the-2021-22-term> [<https://perma.cc/64DW-2U7K>].

⁸ See, e.g., Albert Hunt, *Republicans Should Know About Politicizing the Supreme Court - They Did it*, THE HILL (Apr. 3, 2022), <https://thehill.com/opinion/judiciary/3257552-republicans-should-know-about-politicizing-the-supreme-court-they-did-it/> [<https://perma.cc/BE6L-ZD3C>]; See also, e.g., James D. Zirin, *The Supreme Court's Partisanship is Becoming Increasingly Difficult to Deny*, THE HILL (Oct. 4, 2021), <https://thehill.com/opinion/judiciary/575076-the-supreme-courts-partisanship-is-becoming-increasingly-difficult-to-deny/> [<https://perma.cc/3D6A-PXDX>].

⁹ *Payne v. Tennessee*, 501 US 808, 844 (1991) (Marshall, J., dissenting).

¹⁰ *Obergefell v. Hodges*, 576 U.S. 644, 719 (2015) (Scalia, J., dissenting).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

While changes to the Court and its precedent are not a novel feature of the law,¹¹ there is evidence that suggests public perception of the Court’s legitimacy is on the decline. Recent polling indicates that the public is beginning to identify the Court with broader prevailing political narratives ranging from abortion to immigration.¹² Yet, other polls suggest that, because Congressional and Executive trust is so low, the public is nevertheless more willing to trust the Supreme Court to offer final decisions on contentious areas of both policy and law.¹³

This study aims to illustrate a more universalist picture of the Supreme Court than Scalia or Marshall would propose. In short, building off Justice Barrett’s quip that the Supreme Court is “not comprised of a bunch of partisan hacks,”¹⁴ we propose that legal behavior can be understood by the innate psychological framing and preferences individuals hold. To do so, we engineered a deep neural network (DNN) called SCOTUS_AI to predict Supreme Court outcomes through a sentiment analysis of government briefs. We aim to demonstrate that artificial intelligence can outperform traditional methodologies by identifying patterns in human language not readily available to even experienced scholars. Finally, this study will use SCOTUS_AI to cast predictions on several upcoming Supreme Court cases.

¹¹ David Schultz, *The Supreme Court Has Overturned Precedent Dozens of Times in The Past 60 Years, Including When It Struck Down Legal Segregation*, THE CONVERSATION (Sept. 20, 2021), <https://theconversation.com/the-supreme-court-has-overturned-precedent-dozens-of-times-in-the-past-60-years-including-when-it-struck-down-legal-segregation-168052> [<https://perma.cc/DX7G-TZSZ>].

¹² *Public’s Views of Supreme Court Turned More Negative Before News of Breyer’s Retirement*, PEW RESEARCH CENTER (Feb. 2, 2022), <https://www.pewresearch.org/politics/2022/02/02/publics-views-of-supreme-court-turned-more-negative-before-news-of-breyers-retirement/> (reporting that “[f]avorable ratings of the Supreme Court have declined sharply in the past year.”) [<https://perma.cc/GUZ2-HM7L>]; Christopher J. Casillas, et. al, *How Public Opinion Constrains the U.S. Supreme Court*, 55 AM. J. OF POL. SCI. 74, 86 (2010) (explaining that “the prevailing tides of public sentiment create an active, meaningful constraint...”).

¹³ Ephrat Livni, *Americans Trust the Supreme Court more than other Government Branches*, QUARTZ (Oct. 26, 2019), <https://qz.com/1735709/americans-trust-supreme-court-more-than-other-government-branches/> [<https://perma.cc/3HF8-87K6>].

¹⁴ Dominick Mastrangelo, *Barrett: Supreme Court ‘Not Comprised of a Bunch of Partisan Hacks’*, THE HILL (Sep. 13, 2021), <https://thehill.com/homenews/571935-coney-barrett-supreme-court-not-comprised-of-a-bunch-of-partisan-hacks/> [<https://perma.cc/F67E-BQK5>].

II. Literature Review

Of the numerous theses of Supreme Court behavior, two tend to dominate academic studies: institutionalism and psychoanalysis.¹⁵ These models, while not necessarily incompatible, represent a larger, ever-evolving dichotomy accelerated by new technologies.¹⁶ The former reasserts a traditional legal framework focused on predicting court behavior through a contextual analysis of case precedent, rules, and substantive arguments. The latter asserts that human behavior can be represented in a series of advanced mathematical functions, predictable given sets of environmental externalities and psychological cues.

III. Institutional Models

In his treatise on law, Holmes famously sets forth the mode of the institutionalist theory: “The means of the study are a body of reports, of treatises, and of statutes, in this country and in England, extending back for six hundred years, and now increasing annually by hundreds.”¹⁷ Along similar lines, Justice Breyer observes that the fundamental job of a judge is to “interpret or to apply the legal phrases that we find either in a statute or in the Constitution itself.”¹⁸ For Holmes and Breyer, the study of law is to reasonably apply rules through precedent and other internal, legal devices.¹⁹ Of course, debates emerge challenging the appropriate vehicle to interpret these phrases: for the Constitution specifically, conservatives tend to prefer originalism and textualism,²⁰ while

¹⁵ See Tracey George & Lee Epstein, *On the Nature of Supreme Court Decision Making*, 86 AM. POL. SCI. REV. 323 (1992) (explaining that the “institutionalist” and psycholinguistic is also referred to as the “legal” and “extralegal” model debate); See also Oxford University Press, *THE PSYCHOLOGY OF JUDICIAL DECISION MAKING* (David E. Klein & Gregory Mitchell, eds. 2010) (“...unlike political science models, which emphasize the pursuit of legal and policy preferences... psychology highlights the importance of group processes and how issues of power and reputation also contribute to group formation on the Supreme Court.”).

¹⁶ See generally David William Aha, *A Study of Instance-based Algorithms for Supervised Learning Tasks: Mathematical, Empirical, and Psychological Evaluations*, in UC IRVINE, ICS TECHNICAL REPORTS 210 (1990); Cf., e.g., N. Sivaranjani et. al, *Predicting the Supreme Court Decision on Appeal Cases Using Hierarchical Convolutional Neural Network*, 24 INT’L J. OF SPEECH TECH. 643, 643–50 (2021) (showing that the application convolutional technologies that have the machine generate features is removing the need for cohesive theory altogether).

¹⁷ Holmes, *supra* note 1, at 1.

¹⁸ BREYER, *supra* note 4 at 64.

¹⁹ George & Epstein, *supra* note 14; See, e.g., Leah Litman, *Remarks to Hasting Law Journal’s 2019 Symposium*, 70 U.C. HASTINGS L. J. 1225, 1227 (2019) (explaining that the commitment to stare decisis for Justice Kennedy has a broader implication; that is, “a willingness to uphold the decisions of the institution, and to make the institution bigger than any of the individual people who are a part of it.”); See generally JEFFREY ALLAN SEGAL & HAROLD J. SPAETH, *THE SUPREME COURT AND THE ATTITUDINAL MODEL REVISITED* 44–85 (2008).

²⁰ See generally Robert Post & Reva Siegel, *Originalism as a Political Practice: The Right’s Living Constitution*, 75 FORDHAM L. REV. 545 (2006); STEVEN G. CALABRESI, *ORIGINALISM: A QUARTER-CENTURY OF DEBATE* (2007).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

liberals prefer seeing the Constitution as a “living document.”²¹ There are also exceptions to this dichotomy: “common good constitutionalism,” for example, is triumphed by some conservative academics,²² despite occasionally disputing originalism.²³

However, it is this basic assumption—that the legal rulings can be understood through a set of rules and precedents—that invariably binds otherwise opposed institutionalist views.²⁴ Such a theoretical understanding of the law also translates to similar methodological preferences, with most studies forecasting Supreme Court decisions focused on case characteristics (citations and precedence), expert opinion (the logical, legal coherence of an opinion), and institutional barriers (procedural stance).²⁵ Likewise, some institutional scholars focus on extralegal structural factors, ranging from economic impact, party identities, and other contextual causes (often socioeconomic).²⁶

These methodological approaches align with the claim by institutionalists that adherence to court precedence, *stare decisis*, is necessary to a functional society and therefore an encouraged, altogether occasionally not required,

²¹ See, e.g., Alex Tobin, *The Warren Court and Living Constitutionalism*, 10 IND. J. OF L. SOC. EQUALITY 221, 223 (2022) (explaining that the Warren court in particular used “[l]iving constitutionalism” to “reflect a diverse America that was unable to take part in the founding.”).

²² Conor Casey, ‘Common Good Constitutionalism’ and the New Debate over Constitutional Interpretation in the United States, 4 PUB. L. 765 (2021); See, e.g., Conor Casey & Adrian Vermeule, *Myths of Common Good Constitutionalism*, 45 HARV. J. L. & PUB. POL’Y 103, 105 (2022) (“The hallmark of the classical legal tradition is that law, to be law in the focal sense of that term, must be rationally ordered to the common good of the political community.”).

²³ See Josh Hammer, *Common Good Originalism: Our Tradition and Our Path Forward*, 44 HARV. J. L. & PUB. POL’Y 917, 959 (2021) (“None of the three general forms of originalism on the menu today—progressive, libertarian, or positivist conservative—has been anywhere near successful at retaining and promoting the substantive ends of conservatism... But common good originalism presents our best chance yet for a truly, substantively conservative jurisprudence.”). Cf., Casey & Vermeule, *supra* note 21, at 126 (arguing that “originalism or textualism or positivist interpretation generally will reach the same result as classical legal interpretation.”).

²⁴ Theodore W. Ruger et al., *The Supreme Court Forecasting Project: Legal and Political Science Approaches to predicting Supreme Court Decision Making*, 104 COLUM. L. REV. 1150, 1152 (2004) (“Some of these accounts explore the potential constraints on judicial discretion supplied by case law, text, and history, others focus on broader interpretive theories, others highlight the Justices’ individual policy preferences or social backgrounds, and others regard the Court and its Justices as operating strategically in a complex institutional setting that can influence outcomes... and many scholars in both disciplines regard several, if not all, of the aforementioned factors as important influences on judicial decision making.”).

²⁵ See *id.* at 1156.

²⁶ Kevin T. McGuire & James A. Stimson, *The Least Dangerous Branch Revisited: New evidence on Supreme Court responsiveness to public preferences*, 66 J. OF POLITICS at 1018 (2004); See also Ruger et al., *supra* note 24, at 1152 (explaining that political scientists tend to favor “attitudinal and institutional explanations” over “doctrine, text, and legal principle.”).

finding.²⁷ Even Justice Scalia, an originalist who was notable for opining against several major precedents including *Roe v. Wade*, consistently emphasized the importance of *stare decisis*: “Originalism, like any other theory of interpretation... must accommodate the doctrine of *stare decisis*; it cannot remake the world anew.”²⁸

As a result, much effort has been focused on generalized academic opinions on the merits of legal arguments. Despite observations, such as by Ruger, that expert predictions are often either inferior or equal to simply predicting in favor of the petitioner, institutionalism nevertheless persists both for its ability to extract meaningful effects of rulings, and to understand the reasoning behind such rulings, even if such explanations are simply pretexts for larger sociological or psychological phenomena.²⁹ Simply put, institutionalists look at a given context, and suggest what would be a logical conclusion given the facts and rules.

III. Psycholinguistic Models

Psychoanalysis provides a second mode of understanding the law, analyzing underlying, often subconscious, motivational incentives or preferences that can affect the perception of an individual case or policy.³⁰ Functionally,

²⁷ H. Campbell Black, *The Principle of Stare Decisis*, 34 AM. L. REG., 745, 745 (1886) (“*Stare decisis*... to abide by the precedents and not to disturb settled points. Its meaning is, that when a point of law has been once solemnly and necessarily settled by decision of a competent court, it will no longer be considered open to examination...”); See also Frederick Schauer, *Stare decisis: Rhetoric and Reality in the Supreme Court*, 2018 SUP. CT. REV., 121, 126 (2019) (“Here the expectation embodied in the idea of *stare decisis* is that judges of a court will, presumptively even if not conclusively, follow the previous decisions of that court... even if and when they think the previous decisions are mistaken.”); Ilya Shapiro & Nicholas Mosvick, *Stare Decisis after Citizens United: When Should Courts Overturn Precedent*, 16 NEXUS J. L. & PUB. POL’Y, 121, 124 (2010) (“*stare decisis* does not require courts to extend or preserve a prior decision that misstated or misapplied the law.”).

²⁸ Autumn Fox & Stephen McAllister, *An Eagle Soaring: The Jurisprudence of Justice Antonin Scalia*, 19 CAMPBELL L. REV., 223, 303 (1997).

²⁹ Andrew D. Martin et al., *Competing approaches to Predicting Supreme Court Decision Making*, 2 PERSPS. ON POL. 761, 761 (2004).

³⁰ Joseph Goldstein, *Psychoanalysis and Jurisprudence: On the Relevance of Psychoanalytic Theory to Law*, 77 YALE L. J. 1053, 1053 (1968); Cf. Morris Eagle, *Psychoanalysis and the Law*, 48 INT’L J. OF LAW AND PSYCHIATRY 57, 58 (2016) (Freud, like Nietzsche, views the law in that of a debt discourse, arguing that law is a reflection of collectivized violence on individuals; this is particularly dangerous as the law can then provide a pretext to incentivize “the pleasure of doing violence.”). *Id.* at 57 writes: Freud’s position is congruent with Nietzsche’s argument that the framework for the relationship between crime and punishment reflected in the law is based on the relationship between debt and payment or between debt and restitution. On the societal level, payment or restitution for unpaid debt is made in the form of punishment at the hands of society. On the intrapersonal or intrapsychic level, payment is made in the form of guilt, a way of punishing or inflicting injury upon

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

psychoanalysis suggests that human behavior is best understood by unconscious motivations, often created during a younger, “psychosocial” phase of childhood.³¹ These unrecognized impulses, psychoanalysts argue, can reflect decision making capabilities in real world structures.³²

For the purposes of this paper, an important contrast between institutionalism and psychoanalysis is a distinction in methodology; institutionalists, as we noted, prefer easily articulable theories of law that reside in the legal vehicles of treaties and precedent.³³ Psychoanalysis, however, seeks to examine the underlying reason as why actors prefer vehicles of interpretation.³⁴ Psychoanalysis does not necessarily disregard, for example, historical precedence, but instead reinterprets it as a function of unconscious resistance to change.³⁵ Goldstein writes:

there is in law... a rich residue which each generation preserves from the past, modifies for the present, and leaves for the future... The congruence of their concern for man, his mind, his behavior, and his environment may justify this assertion of mutual relevance.³⁶

Goldstein thus suggests that *stare decisis*, for example, is merely an incidental result of a deeper psychological incentive to maintain what is deemed

oneself by oneself. Insofar as guilt is the internalized product of societal prohibitions in the form of a superego structure, one can think of it as an indirect form of societal punishment as payment for the debt incurred by committing a transgression.

³¹ Stephen Frosh, *Psychosocial Studies with Psychoanalysis*, 12 J. PSYCHOSOCIAL STUD., 101, 101–14 (2019).

³² Goldstein, *supra* note 30, at 1061.

³³ Ruger et al., *supra* note 24, at 1152.

³⁴ Costas Douzinas, *Psychoanalysis Becomes the Law: Notes on An Encounter Foretold*, 20 LEGAL STUD. 323, 323 (1996).

³⁵ See Douzinas, *supra* note 34, at 323 (“If the law expresses the power and the logic of institution, tradition and reason, our personal experiences, our history with its traumas and symptoms, determine the way in which we attach ourselves to this logic. Attention to the emotional aspects of life in the law and to their hermeneutical value has been reinforced by the recent turn to psychoanalysis.”); Cf. Peter Goodrich, *Maladies of the Legal Soul: Psychoanalysis and Interpretation in Law*, 54 WASH. & LEE L. REV. 1037 (1997) (explaining that Freud’s view, analogizing to the Oedipus complex, saw the law similar to a parental authority in setting appropriate boundaries: “The Oedipus complex presents the initial encounter of the subject with an absolute limit, an authority or law. The myth can thus be taken to exemplify the subjective structure of recognition of authority and obedience to, or (neurotic) revolt against, law. In this sense, the son embodies the conflict that everyone faces between a remorseful obedience to law and transgression of it. At the level of the subject, the Oedipal structure is one of conflict between desire and law. It should be noted, for that reason, that it not only banishes desire to the unconscious, but also defines law by reference to its prohibition of desire or, more simply, to an unconscious erotic drive. To kill your father or sleep with your mother is a consciously incomprehensible or simply unthinkable act.”).

³⁶ Goldstein, *supra* note 30, at 1053.

as secure.³⁷ The fruit of psychoanalysis, Goldstein argues, is that it forces “into view conflicts between existing rules and preferred values which [decisionmakers] may not see or may not wish to acknowledge.”³⁸ As early as 1881, before Freud’s publications, even Oliver Wendell Holmes acknowledged the influence of emotions:

The life of the law has not been logic: it has been experience. The felt necessities of the time, the prevalent moral and political theories, intuitions of public policy, avowed or unconscious, even the prejudices which judges share with their fellow-men, have had a good deal more to do than the syllogism in determining the rules by which men should be governed.³⁹

A second important focal point is the internal reasoning for each case opinion. For the psychoanalytic model, the merit of reasoning is predominantly a function of internalized or subconscious drives, with legal rules or tests acting as pretexts for a predetermined, preferred outcome.⁴⁰ Institutionalists, in contrast, emphasize the Court’s reasoning as fundamental to its decision making.⁴¹ While there are “cynics” amongst institutionalists that point to flawed patterns of

³⁷ Goldstein, *supra* note 30, at 1058; *See also* Henry Paul Monaghan, *Commentary: The Constitution Goes to Harvard*, 13 HARV. C.R. L. REV. 117, 130 (1978) (speculating that “[t]his is not purely (although it is, no doubt, in part) a psychological mind set resistant to change, one comfortable with the past, ‘any’ past, but fearful of the future.”); *But see* Marshall Kapp, *Psychoanalysis Applied to the Law: Book Review*, J. OF PSYCHIATRY & L., at 266 (1984) (commenting that the literature may suggest that *stare decisis*, and similar legal doctrines, may not be fully explained by subconscious motives: “[this] does not mean that we should abandon concepts of *stare decisis*... we most certainly should not... it is the mind and heart, as well as our inductive and deductive mental powers, that determine the shape of the laws under which we must live.”); *But c.f.* Goldstein, *supra* note 30, at 1062 (“Psychoanalysis cannot provide ‘the ultimate ends for the moral aspects of personal, social or political behavior. But . . . contributions toward clarification and organization, in the framework of a given system of valuations, or more specifically in the framework of given moral codes . . . can be gained simply and directly from psychoanalytic knowledge.”).

As all three authors argue, there is likely some form of psychological persuasion occurring, even if not completely explanatory. Because motivation can be alternatively explained in numerous ways, as Goldstein points out, psychoanalysis simply offers a single consistent framework of phenomena.

³⁸ Goldstein, *supra* note 30, at 1060.

³⁹ *Id.* at 1056.

⁴⁰ Kristen Konrad Tiscione, *Feelthinking like a Lawyer: The Role of Emotion in Legal Reasoning and Decision-Making*, 54 WAKE FOREST L. REV. 1159, 1184 (2019) (“all ‘decision-making requires the integrated deployment of both the automatic and deliberative systems (and cognition and emotion) working together and mutually supporting one another.”).

⁴¹ Jeff A. King, *Institutional Approaches to Judicial Restraint*, 28 OXFORD J. OF LEGAL STUD. 409, 409–10 (2008).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

reasoning, even these theorists maintain that the perceived merit to reasoning is central to the Court's final decision.⁴² Moreover, understanding this internal reasoning requires a lengthy, time consuming analysis, often involving numerous hours attempting to reconcile nuances in seemingly contradicting case precedents.⁴³ As a result, institutionalism's methodological approach tends to support a hyper-specialized view of Supreme Court reasoning, with experts in each field carefully examining the rules applied to each case. Psychoanalytical reasoning, in contrast, is largely universal.

The similarities between different types of institutionalists can also be seen between the social scientists, whom often examine the law by categories of 'civil rights' and 'wealth distribution,' whereas the legal theorists carefully demarcate categories of law by specific labels applying to the rules, not effect, such as 'search and seizure' instead of 'civil rights' generally;⁴⁴ and while both differ in method, they both assume the predominant issue that affects the decision of the policymaker is the one immediately at hand.⁴⁵ Moreover, because both fields are deeply heterogeneous, specific distinctions are constrained by these generalities. Despite these differences, the shared assumption by both allow some scholars to incorporate both into decision-making forecasts: the attitudinal theory of judicial decision making, for example, argues that political affiliation is the most accurate indicator of outcome.⁴⁶ Finally, while the psychoanalytic model argues against the institutionalist assumption that the merit of the issue is an important variable, it may be, as some scholars have suggested, that the perceived value of legal merit itself is that of a psychological nature, and thus 'merit' is only predictive in that it mediates subconscious desires.⁴⁷ Thus, because both fields could potentially intersect, useful models will be able to compare and contrast the variables used to determine which are most efficient in producing outcomes.

⁴² See, e.g., Peter Suber, *Legal Reasoning After Post-Modern Critiques of Reason*, 3 J. LEGAL WRITING INST. 21, 22 (1997) ("I argue that reasoning from given premises and rules of inference can be rigorous in just the ways established by contemporary logic, but that the justification of our ultimate premises and rules may be ideological or question-begging in just the ways pointed out by the post-Enlightenment critiques.").

⁴³ Ruger et al., *supra* note 24, at 1153 ("Close reading and analysis of opinion content takes time, and convincing explanation or refutation even longer, placing practical limits on the number of holdings a legal scholar can meaningfully synthesize for analytical purposes.").

⁴⁴ Ruger et al., *supra* note 24, at 1153; See also Jack Goldsmith & Adrian Vermeule, *Empirical Methodology and Legal Scholarship*, 69 U. CHI. L. REV. 153, 153 (2002) ("[Legal scholarship frequently pursues doctrinal, interpretive, and normative purposes rather than empirical ones. Legal scholars often are just playing a different game than the empiricists play . . .]").

⁴⁵ Ruger et al., *supra* note 24, at 1153.

⁴⁶ Isaac Unah & Ange-Marie Hancock, *U.S. Supreme Court Decision Making, Case Salience, and the Attitudinal Model*, 28 L. & POL. 295, 317-18 (2006).

⁴⁷ Donald C. Langevoort, *Ego, Human Behavior, and Law*, 81 VIR. L. REV. 853, 862 (1995) (surveying several studies showing 'merited' legal arguments are often guises of ego and personal desires or experiences).

To test the psychoanalytic thesis, scholars have generally attempted to measure the impact of emotional appeal on Supreme Court outcomes.⁴⁸ One approach, sentiment analysis, asserts that cases can be reframed through oral and written arguments, modifying the appraisal, and thus, the outcome.⁴⁹ Most research focusing on sentiment analysis operates by mining textual data for significant terms and then systematically sorts terms by various categories such as “positive,” “neutral,” and “negative.”⁵⁰ One particular tool of sentiment analysis, the Linguistic Inquiry and Word Count (LIWC) API, has been shown to detect psychological meaning in a number of significant ways, including attentional focus and suggestive relationships.⁵¹ LIWC, which operates by mining text for phrase and syntax frequency, is thus able to comprehend arguments in various settings regardless of context.⁵² Other studies have similarly illustrated LIWC’s effective use, ranging from mining text conversations of vaccines on twitter to predicting cabinet minister votes in Australia.⁵³

⁴⁸ See generally Bryce J. Dietrich et al., *Emotional Arousal Predicts Voting on the U.S. Supreme Court*, 27 POL. ANALYSIS 237, 239–42 (2018); See also Sarah Levien Shullman, *The Illusion of Devil’s Advocacy: How the Justices of the Supreme Court Foreshadow Their Decisions During Oral Argument*, 6 J. OF APP. PRAC. AND PROCESS 271 (2004).

⁴⁹ Yelena Mejova, *Sentiment Analysis Within and Across Social Media Streams*, IOWA RESEARCH ONLINE, 5 (2012) (“As a field of research, [sentiment analysis] is closely related to (or can be considered a part of) computational linguistics, natural language processing, and text mining. Proceeding from the study of affective state (psychology) and judgment (appraisal theory), this field seeks to answer questions long studied in other areas of discourse using new tools provided by data mining and computational linguistics.”). See, e.g., Chanika Ruchini Mudalige et al., *Sigmalaw-ABSA: Dataset for Aspect-Based Sentiment Analysis in Legal Opinion Texts*, INTER. CONF. ON INDUSTR. AND INFO. SYST. (2020); See also, e.g., Isanka Rajapaksha et al., *Rule-based Approach for Party-Based Sentiment Analysis In Legal Opinion Texts*, INT’L. CONF. ON ADVANCEMENTS IN ICT FOR EMERG. REG. (2020); See generally Shila Jawale & S.D. Sawarkar, *Interpretable Sentiment Analysis Based on Deep Learning: An Overview*, PUNE SEC. INT’L. CONF., 65 (2020) (“Sentiment analysis is a way to handle text, images that represent emotion of feeling (emoji etc.), multi-modal data to detect and extract meaningful subjective information.”).

⁵⁰ Jawale & Sawarkar, *supra* note 49, at 65 (“It is generally a positive, neutral, or negative opinion towards an object of interest.”).

⁵¹ Yla R. Tausczik & James W. Pennebaker, *The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods* 29 J. OF LANGUAGE AND SOC. PSYCH. 24, 24 (2009).

⁵² Roger McHaney et al., *Using LIWC to Choose Simulation Approaches: A Feasibility Study*, 111 DEC. SUPP. SYST. 1, 5 (2018).

⁵³ See, e.g., Andranik Tumasjan et al., *Predicting Elections with Twitter: What 140 Characters Reveal about Political Sentiment.*, 4 FORTH INT’L. AAAI CONF. ON WEB. AND SOC. MEDIA 178, 180–82 (2010); see also, e.g., Michael Coleman Dalvean, *The Selection of Cabinet Ministers in the Australian Federal Parliament* 9–10 (2012) (Ph.D. dissertation, Australian National University); See generally Tausczik & Pennebaker, *supra* note 47, at 38 (“LIWC represents only a transitional text analysis program in the shift from traditional language analysis to a new era of language analysis. Newer text analysis will be able to analyze more complex language structure while retaining LIWC’s transparency.”).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

A second technique moves beyond text mining and identifies voice pitch and non-verbal signals in oral hearings. Owens and Wedeking, for example, demonstrate that rhetorical style can often overcome ideological biases among judges.⁵⁴ Legal researchers have also found this general prevalence in specific arenas of the law. Sween (2009), for example, finds that despite ideological divides, the Supreme Court acted consistently in preferring broad sweeping principles over appellate circuit nuances in patent cases where the latter failed to apply “ordinary” language.⁵⁵ As Sween notes in *eBay Inc. v. MercExchange* (2006), eBay’s ability to rhetorically frame the Appellate Court’s injunction as “unusual,” “exceptional,” and “rare,” rather than focus on the merits of the actual injunction, successfully persuaded the court to overturn precedence.⁵⁶ Likewise, researchers have found relations between non-verbal psychology and the jurisprudence in family, privacy, and public law.⁵⁷ While LIWC has also been shown to be weaker in certain situations, such as when language is inconsistently used during informal settings,⁵⁸ several studies seem to indicate that LIWC is appropriate for the Supreme Court. As Ballingrud finds, Supreme Court opinions scraped and piped into LIWC suggest that the risk focus of conservative judges was highly predictive of their judicial decision-making, especially in criminal procedural cases.⁵⁹ Likewise, evidence also suggests that frequent, emotive negative dissents strongly correlate to eventual policy change, either within the court’s docket or in public debate.⁶⁰ As a result, LIWC has been useful in measuring emotive content both in the Supreme Court and across the social sciences.

⁵⁴ See Ryan J. Owens & Justin Wedeking, *Predicting Drift on Politically Insulated Institutions: A Study of Ideological Drift on the United States Supreme Court*, 74 J. OF POL. 487, 496 (2012).

⁵⁵ Gretchen Sween, *Who’s Your Daddy - A Psychoanalytic Exegesis of the Supreme Court’s Recent Patent Jurisprudence*, 7 NW. J. OF TECH. AND INTELL. PROP. 204, 210 (2009).

⁵⁶ *Id.* at 210.

⁵⁷ See Tess Wilkinson-Ryan, *Psychology and the New Private Law*, in THE OXFORD HANDBOOK OF THE NEW PRIV. L. 124 (2020); See generally Fiona E. Raitt & M. Suzanne Zeedyk, *The Implicit relation of Psychology and Law: Women and Syndrome Evidence*, ROUTLEDGE 1 (2000).

⁵⁸ Tausczik & Pennebaker, *supra* note 51, at 30 (“Despite the appeal of computerized language measures, they are still quite crude. Programs such as LIWC ignore context, irony, sarcasm, and idioms. The word ‘mad,’ for example, is currently coded as an anger word. When people say things such as ‘I’m mad about him,’ or ‘He’s as mad as a hatter’ the meaning and intent of their utterances will be miscoded. LIWC, like any computerized text analysis program, is a probabilistic system.”). See, e.g., Erin A. Vogel & Cornelia (Connie) Pechmann, *Application of Automated Text Analysis to Examine Emotions Expressed in Online Support Groups for Quitting Smoking*, 6(3) J. OF THE ASS’N FOR CONSUMER RSCH, 60 (2021) (explaining that, “text analysis can only capture the emotions individuals are willing to express publicly. In addition, LIWC’s dictionary of emotions is not fully comprehensive and lacks specific positive emotions.”).

⁵⁹ Gordon Ballingrud, *Ideology and risk focus: Conservatism and opinion-Writing in the U.S. Supreme Court*, 102 SOC. SCI. QUART. 281, 288, 293 (2020).

⁶⁰ Amanda C. Bryan & Eve M. Ringsmuth, *Jeremiad or Weapon of Words? The Power of Emotive Language in Supreme Court Dissents*, 4 J. OF L. AND COURTS 159, 160–64 (2016).

In the context of the Supreme Court, the second method of identifying non-verbal signals has a number of weaknesses. First, the only data available to scholars comes from oral hearings, which eliminates any computational analysis of facial expressions. While several scholars offer evidence that suggests this method has some merit,⁶¹ it ignores one of the largest, often cited as most impactful processes of the legal disputes: briefs.⁶² While scholars have debated the actual impact of the quality of merit briefs, such “quality” is usually interpreted in the terms of institutionalism; as a result, the “quality” of a merit brief in a psychoanalytic lens as it relates to the predictive power on an individual case remains largely untested or disregarded entirely.⁶³ A second problem with non-verbal signaling is methodological: even if there is sufficient data to draw a statistically valid analysis, scholars are traditionally required to qualitatively sort expressions.⁶⁴ Because oral hearing data can be sparse, new studies that use non-verbal signaling will need to either create a more comprehensive theoretical

⁶¹ Dietrich et al., *supra* note 48, at 572; Owens & Wedeking, *supra* note 61, 498–99; See Ryan C. Black et al., *Emotions, oral arguments, and Supreme Court Decision Making*, 73(2) J. OF POL. 572, 573 (2011) (Thus, as scholars continue to build models of the Court’s decision-making process they must account for what transpires during these proceedings, including the justices’ emotional state as they move toward decisions) [hereinafter Black et al., *Emotions, Oral Arguments*].

⁶² See Stefanie A. Lindquist & David E. Klein, *The Influence of Jurisprudential Considerations on Supreme Court Decisionmaking: A Study of Conflict Cases*, 40 L. & SOC. REV. 135, 137 (2006) (explaining that the government has significant influence during the briefing process: “Some research indicates that the SG’s success continues at the merits stage as well, whether as party or amicus... The SG’s influence may be related to a number of factors. For instance, justices may give greater deference to the views of the executive branch than to those of other parties. McGuire (1998) has argued that the SG’s success is attributable largely to the expertise of lawyers in the SG’s office.”); See also Paul M. Collins et al., *The Influence of Amicus Curiae briefs on U.S. Supreme Court Opinion Content*, 49 L. & SOC. REV. 917 (2015) (explaining the impact of amicus curiae briefs: “We find that the justices borrow more language from high quality amicus briefs that, in turn, better enable them to author high quality majority opinions. Justices also incorporate more language from amicus briefs that repeat arguments advanced in other information sources, suggesting they are more likely to view that information as credible. Moreover, the justices adopt more language from amicus briefs that correspond to their ideological preferences, and those filed by high status interest groups.”).

⁶³ Lindquist & Klein, *supra* note 62, at 156 (“We initially attempted to develop a valid way of measuring the quality of an opinion’s legal arguments, and we hope that we or some other scholars will do so in the future, but we were not able to for this project.”); *But see* Kevin T. McGuire, *Explaining Executive Success in the U. S. Supreme Court*, 51 POL. R. QUART., 505, 522 (1998) (explaining the government may simply be incidentally more merited, rather than able to manipulate the merits from a position of power: “... the solicitor general’s advantage—indeed, it’s only advantage and a rather weak one, at that—is its command of litigation expertise. The difference between the solicitor general and other repeat players, it turns out, is evidently one of degree, not of kind.”).

⁶⁴ See, e.g., Black et al., *supra* note 61, at 574 (noting the distinction between “pleasant” and “unpleasant” language towards a particular party’s attorney). See also, e.g., Dietrich et al., *supra* note 48, at 572–75.

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

framework to allow consistent identification by researchers, or use computational methods, such as convolutional neural networks, to more rigorously record data.⁶⁵

Finally, it is important to note that, unlike institutionalists, psychoanalytic research is often only largely suggestive; in part, this is because psychoanalytic methodologies, such as sentiment analysis, struggle to concretely demonstrate a relationship to the actual subconscious motives so deeply embedded in psychoanalysis.⁶⁶ Sentiment analysis also cannot describe the underlying values, good or evil, to a system.⁶⁷ While neuroscience research has begun to support the psychoanalytic model for directional support on decision making, most empirical evidence, such as sentiment analysis, only offers strong correlative relationships. As a result, the expectations of a psychoanalytic model are not necessarily mutually exclusive to the institutionalists; indeed, it may be that the rules so carefully scrutinized by institutionalists do affect Court outcomes, but that such a relationship is that of a mediator, rather than original causal agent. For example, a rule may imply certain meanings or connotations that interact with the subconscious desires or fears of a certain Justice, thereby making the rule's merit itself seem to modify behavior while in reality it is the connotation of the rule.⁶⁸ That is, if institutional agents have emotional responses related to their role and

⁶⁵ See, e.g., Samir Undavia et al., *A Comparative Study of Classifying Legal Documents with Neural Networks*, PROC. OF THE FEDERATED CONF. ON COMP. SCI. & INFO. SYST. 515, 516 (2018) (explaining how a convolutional network could work in legal document sorting); Cf. N. Sivaranjani et al., *Predicting the Supreme Court Decision on Appeal Cases using Hierarchical Convolutional Neural Network*, 24 INTER. J. SPEECH TECH. 643 (2021) (demonstrating how a convolutional network can be used in the Indian Supreme Court to predict case outcomes).

⁶⁶ Frank Emmert-Streib et al., *Utilizing Social Media Data for Psychoanalysis to Study Human Personality*, 10 FRONT. IN PSYCH., 1, 3 (2019) ("It is clear that a psychoanalysis is profoundly more difficult than a sentiment analysis, which merely tries to determine emotional or opinion categories."); Bo Pang & Lillian Lee, *Opinion Mining and Sentiment Analysis*, 2 FOUND. & TRENDS IN INFO. RETRIEVAL, 1, 13 (2008) (Reiterating the problematic nature of conflating context and sentiment: "In general, sentiment and subjectivity are quite context-sensitive, and, at a coarser granularity, quite domain dependent (in spite of the fact that the general notion of positive and negative opinions is fairly consistent across different domains).

⁶⁷ Goldstein, *supra* note 30, at 1059 ("Nothing in psychoanalytic theory, for example, can supply the moral values which should inform the law's decision in the legislative debate.").

⁶⁸ See Goodrich, *supra* note 35, at 1038 ("It is through symbols and, more broadly, through images of social place, that the subject recognizes and forms affective attachments to law. The subject of legal authority is bound to law far more strongly by identificatory images or phantasms of a shared substance, by interior and self-imposed limitations, than by the external dictate of positive law."); *But see* Goldstein, *supra* note 30, at 1063 (explaining that "unequivocal condemnation of casual psychoanalytic speculations about the mental lives of particular individuals," must be noted, as psychoanalysis can "potentially destructive" or counterintuitive if, for example, "a teacher examining the decision in a famous attempted murder case to suggest that the defendant was revealing his sexual impotence when he shouted, 'It won't fire. It won't fire,' as he held an unloaded pistol at his estranged wife's head and pulled the trigger.") That is, Goldstein, *supra* note 30, is an actual metaphysical analysis of a personality, instead of a motivator for an action, must involve extensive clinical experience between a practitioner and patient).

profession, those reactions can be used to predict their corresponding actions.⁶⁹ As other scholars have noted, issues such as gay marriage and abortion often provoke emotional connotations and influence decision making.⁷⁰ In contrast, it may be that Justices see the rules as a vacuum, especially on less contentious issues. There is also the possibility that there is a mixed relationship, with the rules mediating some of the psychological impact, but with externalities such as public pressure mediating the rest. Thus, a psychoanalytical model is best analyzed as a relative figure compared against institutionalism.

Another implication to the psychoanalytic model is the unique syntax found in legal briefs; for example, as Martinez, Mollica, and Gibson suggest, lawyers may “choose to write in a complex manner to convey their priorities,” using the brief to signal to their peers.⁷¹ As psycholinguistics might also suggest, it may be that lawyers do not choose to select these personal incentive structures, but instead are burdened with a “curse of knowledge”—that is, instead of aiming for communicative precision, lawyers are simply replicating systems they know.⁷² It may be those systems, and not the lawyers themselves, that superimpose their value criterion. As a result, because conclusions drawn from evidence of a psychoanalytic framework are so diverse, scholars must compare the relative strength of the model against opposing models.

IV. Predictive Algorithms in Court Behavior

Historically, artificial intelligence (AI) has had minimal use in the law outside of researching case precedent.⁷³ This is in part, as Sunstein notes, because of the inability of AI to reason by analogy; that is, to connect larger thematic elements of legal reasoning on a case-by-case basis.⁷⁴ However, when AI is used

⁶⁹ Icek Ajzen, *From Intentions to Actions: A Theory of Planned Behavior*, in ACTION CONTROL 11, 27 (1985); See also Artyom Zinchenko et al., *Emotion and goal-directed behavior: ERP evidence on cognitive and emotional conflict*, 10 SOC. COG. & AFF. NEUROSCIENCE 1577–87 (2015); See generally Martha Nussbaum, *Emotion in the Language of Judging*, 70 ST. JOHN’S L. REV. 23, 24 (1996).

⁷⁰ Ryan C. Black et al., *The Role of Emotional Language in Briefs Before the U.S. Supreme Court*, 4 J. OF L. AND CTS. 377–407 (2015) [hereafter, Black et al., *The Role of Emotional Language*].

⁷¹ Eric Martinez et al., *Poor writing, Not Specialized concepts, Drives Processing Difficulty In Legal Language*, 224 COGNITION, at 6 (2021).

⁷² *Id.* See, e.g., Yasuhiro Ozuru et al., *Prior Knowledge, Reading Skill, and Text Cohesion in The Comprehension of Science Texts*, 19 LEARNING & INSTRUCTION 228–42 (2009) (explaining the unique role of jargon in science texts).

⁷³ See Bruce G. Buchanan & Thomas E. Headrick, *Some Speculation about Artificial Intelligence and Legal Reasoning*, 23 STAN. L. REV. 40 (1970).

⁷⁴ Cass Sunstein, *Of Artificial Intelligence and Legal Reasoning*, at 7 (2001) (University of Chicago Public Law & Legal Theory Working Paper) (“But the more extravagant claims on behalf of artificial intelligence in law are based on a crude picture of legal reasoning, one that disregards the need to root judgments of analogousness, or disanalogousness, in judgments of principle and

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

in the context of large datasets it can not only measure complicated trends more accurately than traditional statistical analysis, but also transcends the abilities of human researchers to notice, detect, and understand patterns in the data.⁷⁵ In the law this effect is magnified, as research on human cognition has shown that expert opinion accuracy generally decreases, not increases, with more information.⁷⁶ Unlike machines that have defined thresholds of considering efficient patterns, human researchers often either become distracted by irrelevant information or offer overly simplistic explanations to fit the maximum amount of data.⁷⁷ Experts in particular are especially vulnerable to this condition; one, for example, are often led away from efficient modeling by heuristics repeated through generations of institutionalist theory.⁷⁸ Humans, moreover, are susceptible to ‘priming,’ or the psychological effect of associating certain words or rules with an either positive

policy.”); See also Richard E. Susskind, *Expert Systems in Law: A Jurisprudential Approach to Artificial Intelligence and Legal Reasoning*, 49 THE MODERN L. REV. 168 (1986); But cf. Nikolaus Kriegeskorte, *Deep Neural Networks: A New Framework for Modeling Biological Vision and Brain Information Processing*, 1 ANNUAL REV. OF VISION SCIENCE 417 (2015) (While beyond the scope of this study, this assumption has been tested by the innovation of “convolutional” AI; that is, AI that can understand differences in images and sight through pixelation differences. Such differences have also been shown to contribute to understanding text documents in highly predictive, albeit seemingly convoluted, ways).

⁷⁵ Wei XU & Liezhong GE, *Engineering Psychology in the Era of Artificial Intelligence*, 28 ADVANCES IN PSYCH. SCI. 1409–25 (2020); See also Kakia Chatsiou & Slava Jankin Mikhaylov, *Deep Learning for Political Science*, SAGE HANDBOOK OF RESEARCH METHODS IN POLI. SCI. & INT’L. R. 1053–78 (2020); See generally Robert W. Blake et al., *Impact of Artificial Intelligence on Engineering: Past, Present and Future*, 104 PROCEDIA CIRP 1728–33 (2021).

⁷⁶ Ruger et al., *supra* note 24, at 1161 (“By contrast, the legal experts were unlikely to consider all of the Court’s decisions over the prior eight terms in reaching their predictions. The nature of legal study—focused as it is on leading cases—predisposes legal experts to focus on a handful of salient cases, rather than attempt to weigh all cases equally. Even if they wanted to, basic cognitive limitations would prevent the human experts from systematically and equivalently taking account of every case previously decided by this natural court.”).

⁷⁷ *Id.* at 1186 (“Rather than conferring an advantage, perhaps the experts’ ability to consider highly particularized information interfered with their predictive success. Considerable research in cognitive psychology has demonstrated the limits of human cognition. People often make poorer rather than better decisions when confronted with more information, because they may shift to simpler, less accurate decision strategies, or may become distracted by less relevant information.”); See also Chris P. Guthrie et. al., *Inside the Judicial Mind*, CORNELL L. FACULTY PUB. 777–830 (2001).

⁷⁸ Ruger et al., *supra* note 24, at 1186 (“The use of heuristics, though adaptive over the long run, may lead to poor judgments in particular cases... Especially in situations... involving large amounts of information and multiple relevant factors [sic] cognitive limits may hamper the experts’ ability to systematically analyze and account for the impact of multiple relevant factors.”); Guthrie et. al., *supra* note 77, at 823–24 (explaining that judges often rely on “anchoring” heuristics, such as age or income, to make decisions even if such metrics were irrelevant or not useful to the legal rule); See, e.g., Troy A. Paredes, *Blinded by the Light: Information Overload and Its Consequences for Securities Regulation*, at 57 (2003) (Washington University School of Law Faculty Working Papers) (explaining, for example, that investors may “actually make less accurate decisions in the face of more information as they adopt less complicated decision strategies in an effort to simplify their investment decision.”).

or negative emotional appeal that induces a corresponding human action.⁷⁹ Scholars have noted the impact of priming and its various instruments in numerous legal situations,⁸⁰ ranging from commercial mediation law,⁸¹ to jury manipulation,⁸² and even to campaign finance regulations.⁸³ AI is not subject to these cognitive limitations, giving researchers a powerful tool to detect seemingly irrelevant patterns and make relatively powerful, highly predictive connections.⁸⁴

With the emergence of new forms of artificial intelligence, such as deep neural networks (DNN), researchers can more effectively solve previously unstructured data problems, such as analyzing audio and video recordings.⁸⁵

⁷⁹ Daniel C. Molden, *Understanding Priming Effects in Social Psychology: What is “Social Priming” and How Does It Occur?* 32 SOC. COGNITION at 3 (2014) (“priming has generally referred to facilitative effects of some event or action on subsequent associated responses... The primary questions pursued by social psychologists studying priming have therefore involved the activation of social representations (e.g., traits, stereotypes, or goals) by exposure to different types of information, and the application of these activated representations in social judgments and behaviors.”); *See also* Mitchell J. Callan et al., *The Effects of Priming Legal Concepts on Perceived Trust and Competitiveness, Self-Interested Attitudes, and Competitive Behavior*, 46 J. OF EXPERIMENTAL SOC. PSYCH., at 326 (2010) (“If psychological representations of everyday legal concepts (e.g., law, legal, lawsuit, lawyer, judge, courts) are associated with the concepts of competition and self-interest—that is, if adversarialism and the pursuit of self-interest are a part of “legal consciousness”—then subtle activation of concepts related to the law should lead to construal of social situations, attitudes, and behavioral responses consistent with self-interestedness.”); *See generally* Constantine Sedikides & John J. Skowronski, *The Law of Cognitive Structure Activation*, 2 PSYCH. INQUIRY, at 169 (1991) (explaining that agents appear to be rational as long as those agents act within established cognitive structures, or “mental representations of general semantic categories.” These can include numerous ideas in different cultures, but ultimately represent how one applies accumulated knowledge.).

⁸⁰ *See generally* Dietrich et al., *supra* note 48, 2–3.

⁸¹ *See generally* Amanda Carruthers, *The Impact of Psychological Priming in the Context of Commercial Law Mediation*, 42 MONASH U. L. REV. 579 (2016).

⁸² Justin Levinson, *Suppressing the Expression of Community Values in Juries: How Legal Priming Systematically Alters the Way People Think*, 73 U. OF CINCINNATI L. REV. 1059, 1059–80 (2005).

⁸³ *See generally* Molly Wilson, *Behavioral Decision Theory and Implications for the Supreme Court’s Campaign Finance Jurisprudence*, 31 CARDOZO L. REV. 679 (2009).

⁸⁴ *See, e.g.*, Ruger et al., *supra* note 24, at 1186–90 (explaining that statistical models are better at correlating and predicting Court outcomes than experts using traditional methodologies); *See also* Katja Grace et al., *Viewpoint: When will AI Exceed Human Performance? Evidence from AI Experts*, 62 J. OF A.I. INTEL. RSCH. 729, 729–754 (2018).

⁸⁵ *See, e.g.*, Jason Anastasopoulos et al., *Political Image Analysis with Deep Neural Networks*, HARV. U. PRESS, at 31 (2017) (“[W]e demonstrate how neural network techniques can be used to understand home style through images. Using convolutional neural networks and empirical analysis of photos posted by members of the House and Senate on their Facebook profiles, we provide evidence that MCs use images to communicate with their re-election constituencies. Neural networks hold a tremendous amount of promise as a means of systematically understanding how images are used as a means of political communication in the digital age.”);

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

DNNs in particular operate analogously to the human brain: a series of neurons pass signals through activation functions that slowly “learn” from received input.⁸⁶ Unlike normal machine learning, which simply generates functions and eliminates inefficient ones,⁸⁷ activation functions in DNNs weigh corresponding functions to find the most efficient means in each individual function.⁸⁸ Thus, unlike machine learning which may favor a specific more efficient function that has certain inefficient aspects, DNNs can increasingly prioritize functions that fit the data while ignoring weaker components.⁸⁹ Figure 1 illustrates how this process, at the most simplistic view, would work for the Supreme Court.

Figure 1. Simple SCOTUS DNN Model

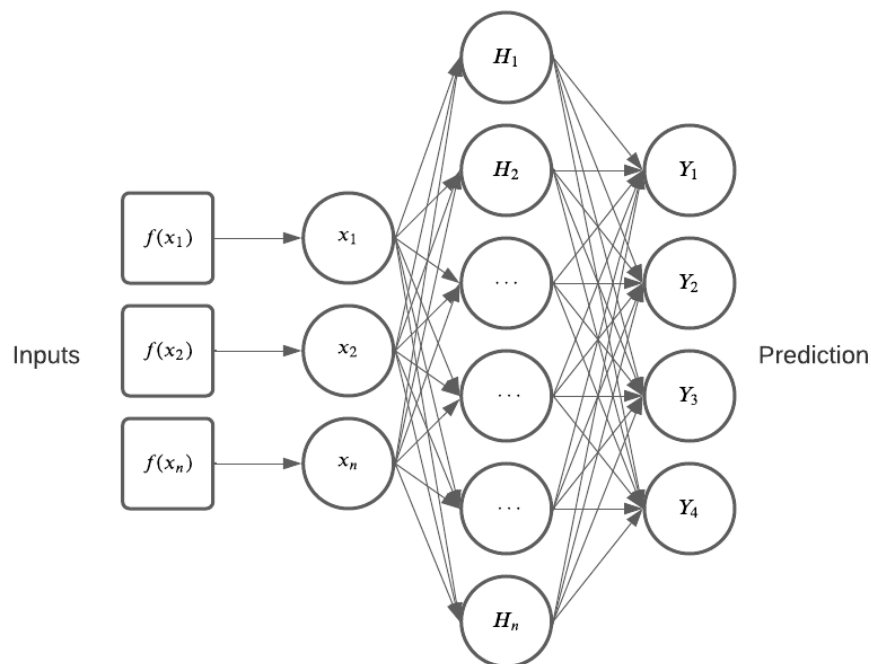
See also Michael Elad et. al., *Another step toward Demystifying Deep Neural Networks*, 117 PROCEEDINGS OF THE NAT. ACAD. OF SCI. 27070–72 (2020); *See generally* Charu C. Aggarwal, *Neural networks and Deep Learning* (2019).

⁸⁶ JOJO MOOLAYIL, *LEARN KERAS FOR DEEP NEURAL NETWORKS: A FAST-TRACK APPROACH TO MODERN DEEP LEARNING WITH PYTHON 3* (2019) (“Upon researching the reasons for this poor performance, an inspiration led to the idea of mimicking the human brain’s biological process, which is composed of billions of neurons connected and orchestrated to adapt to learning new things... When researchers reached the cusp of ML and neural networks, there came the field of [deep learning], which was framed by developing deep neural networks (DNNs), that is, improvised neural networks with many more layers. DL excelled at the new frontiers where ML was falling behind. In due course, additional research and experimentation led to the understanding of where we could leverage DL for all ML tasks and expect better performance, provided there was surplus data availability. DL, therefore, became a ubiquitous field to solve predictive problems rather than just being confined to areas of computer vision, speech, and so on.”). *See generally* Wojciech Samek et al., *Explaining Deep Neural Networks and Beyond: A Review of Methods and Applications*, 109 PROCEEDINGS OF THE IEEE 247–78 (2021).

⁸⁷ *See* MOOLAYIL, *supra* note 86 at 2–3.

⁸⁸ *See Id.* at 3–4.

⁸⁹ *Id.* at 3; *See also* Grégoire Montavon et al., *Methods for interpreting and Understanding Deep Neural Networks*, 73 DIGITAL SIGNAL PROCESSING 1, 1–15 (2018).



The functions of x represent each randomly created function to fit the data, which is passed into each node (formally known as a perceptron) and tested. Each corresponding node, H , in the following hidden layers represent how the DNN tests and builds on accuracy, before finally passing functions into the output layers, Y . These are computed into probabilities, with the highest probability represented in the prediction. The actual number of nodes are subject to set hyperparameters. As displayed above, each function passes through layers of neurons that test and weigh each function, producing the most optimized result.⁹⁰

While DNNs are a relatively new innovation in the field of social sciences,⁹¹ a number of studies have been conducted to engineer algorithms to

⁹⁰ MOOLAYIL, *supra* note 86, at 6 (“...the input data is consumed by the neurons in the first hidden layer, which then provides an output to the next layer and so on, eventually resulting in the final output. Each layer can have one or many neurons, and each of them will compute a small function (e.g., activation function). The connection between two neurons of successive layers would have an associated weight. The weight defines the influence of the input to the output for the next neuron and eventually for the overall final output.”).

⁹¹ Jürgen Schmidhuber, *Deep Learning in Neural Networks: An Overview*, 61 NEURAL NETWORKS, 85 85–117 (2015); *See generally* Michelle Torres & Francisco Cantú, *Learning to See: Convolutional Neural Networks for the analysis of Social Science Data*, 30 POL. ANALYSIS 113, 113–31 (2021).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

predict Supreme Court cases.⁹² In particular, institutionalists lean heavily into the merits of the Court’s arguments, often categorizing cases by field and applying ideological indicators.⁹³ Ruger, for example, provides an institutionalist framework for predicting Supreme Court outcomes, factoring in six variables: the circuit of origin, the identity of the petitioner, the identity of the respondent, ideological direction of a lower court rulings, the presence of constitutional arguments, and the type of issue.⁹⁴ Likewise, Katz *et al.* use the Supreme Court database, which contains approximately 240 categorical variables including case backgrounds, justice-specific preferences, and outcomes to cast predictions.⁹⁵ For psychoanalytical models, Dietrich *et al.* argues that Justices implicitly reveal their preferences through their questions during oral arguments.⁹⁶ To compare accuracy, we sorted selected studies in Table 1.1:

Table 1.1. Model Predictions for Court Outcomes

Theory	Features	Prediction Accuracy	Citation
Institutionalist	Circuit of origin,	75%	Theodore W. Ruger et al.,

⁹² Ranti Dev Sharma et al., *Using Modern Neural Networks to Predict the Decisions of the Supreme Court of the United States with State-of-the-Art Accuracy*, 9490 NEURAL INFORMATION PROCESSING 475–83 (2015).

⁹³ See HOWARD GILLMAN & CORNELL W. CLAYTON, *Beyond Judicial Attitudes: Institutional Approaches to Supreme Court Decision-Making*, in SUPREME COURT DECISION-MAKING: NEW INSTITUTIONALIST APPROACHES 1, 1–5 (Cornell W. Clayton & Howard Gillman eds., 1999). While institutionalism is not homogenous, the attitudinal model has gained favor amongst algorithms for its consistent, measurable properties. See, e.g., Ruger et al., *supra* note 24, at 1163–64 (“[T]he selection of potential variables drew on existing literature about the Court, and, in particular, attitudinalist insights.”).

⁹⁴ Ruger et al., *supra* note 24, at 1163.

⁹⁵ See Daniel Martin Katz et al., *A General Approach for Predicting the Behavior of the Supreme Court of the United States*, PLOS ONE, Apr. 12, 2017, at 4, 12(4): e0174698.

⁹⁶ Bryce J. Dietrich et al., *Emotional Arousal Predicts Voting on the U.S. Supreme Court*, 27 POL. ANALYSIS 237, 238–41 (2018).

	identity of parties, ideological direction of lower court ruling, presence of constitutional arguments, and type of issue.		<i>The Supreme Court Forecasting Project: Legal and Political Science Approaches to predicting Supreme Court Decision Making</i> , 104 <i>Columbia Law Review</i> , at 1150–1210 (2004) [hereinafter <i>Ruger et al.</i> or <i>Ruger</i>].
Institutionalist	Case backgrounds, justice-specific preference, constitutional outcomes, and others.	70.2%	Daniel Martin Katz, Michael James Bommarito & Josh Blackman, <i>Predicting the behavior of the Supreme Court of the United States: A General Approach</i> , Apr. 12, 2017, 12(4): e0174698. [hereinafter <i>Katz et al.</i> or <i>Katz</i>].
Psychoanalytical	Language in oral hearings.	63%	Bryce J. Dietrich, Ryan D. Enos & Maya Sen, <i>Emotional arousal predicts voting on the U.S. Supreme Court</i> , 27 <i>Political Analysis</i> 237 (2018) [hereinafter <i>Dietrich et al.</i> or <i>Dietrich</i>].

Finally, it is important to note Ruger’s observation that a predictive model “does not directly contrast two mutually exclusive theories about what motivates the Court”;⁹⁷ instead, our study focuses on the efficiency of a given method, rather than exclusive, directional, and causal motivator, in predicting the behavior

⁹⁷ Ruger et al., *supra* note 24, at 1161.

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

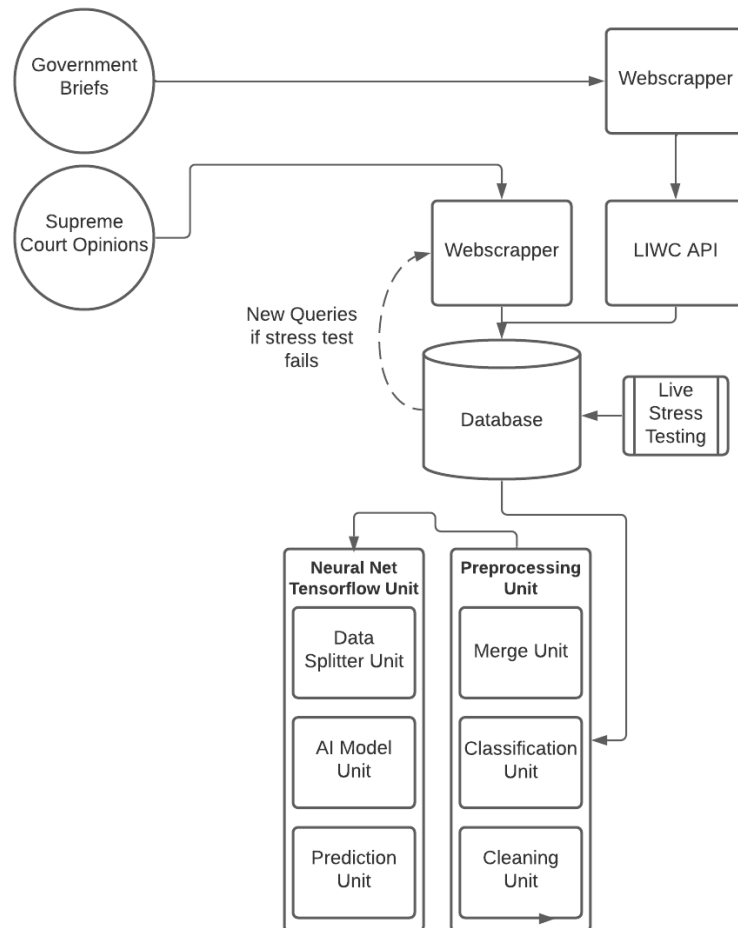
of the Court. Thus, it is the preferable method, not the causal theory, that guides our paper.

V. Methodology

The architecture of our proposed framework, SCOTUS_AI, operates in five central units to predict case outcomes and procedure, as illustrated by Figure 2.⁹⁸

Figure 2. SCOTUS_AI Architecture

⁹⁸ To reproduce this study visit *SCOTUS_AI*, https://www.dropbox.com/s/oj5nvaomcgr4ou/SCOTUS_AI.zip?dl=0. There, the reader can find data sets and instructions.



First, the web scrapers download Supreme Court briefs submitted by the government and parse opinion outcomes from the Supreme Court website. Second, these documents are mined through the Linguistic Inquiry and Word Count (LIWC) API.⁹⁹ Third, the mined data is matched to web scraped Supreme Court verdicts. Fourth, the matched data is manually stress-tested with finalized, preprocessed LIWC data before being returned to the database as features (Appendix A). Fifth, the data is fed to the tensorflow deep neural network (DNN) to create the SCOTUS_AI algorithm. Finally, SCOTUS_AI is used to forecast the outcomes of several recent, important cases. These cases, as illustrated by table

⁹⁹ J.W. PENNEBAKER ET AL., LINGUISTIC INQUIRY AND WORD COUNT: LIWC 2015 (2015).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

2.1, are selected qualitatively by controversy and listed in constitutional reference as drafted by the government.

Table 2.1. Selected Cases

Case Title	Docket Number	Constitutional or Statutory Reference	Arena of Controversy
<i>Dobbs v. Jackson Women’s Health Organization</i>	19-1392	14th Amendment	Abortion
<i>New York State Rifle & Pistol Association Inc. v. Bruen</i>	20-843	2nd Amendment	Firearms
<i>Carson v. Makin</i>	20-1088	1st Amendment	Religious education
<i>Federal Bureau of Investigation v. Fazaga</i>	20-828	1st, 4th, and 5th Amendment	Government Surveillance
<i>United States v. Tsarnaev</i>	20-443	14th Amendment	Death Penalty; Due Process
<i>Shurtleff v. City of Boston</i>	20-1800	1st Amendment	Freedom of Religion, Expression; Government Speech
<i>Students for Fair Admissions v. President and Fellows of Harvard College</i>	20-1199	14th Amendment	Equal Protection; Affirmative Action
<i>George v. McDonough</i>	21-234	38 U.S.C. 7111(a)	Administrative Deference

VI. Variables

The principal purpose of our study is to design an efficient algorithm to predict Supreme Court outcomes using sentiment. For artificial intelligence, we

sort variables by features (the independent variables) and labels (the dependent variables).¹⁰⁰

For features, LIWC categorizes documents through a number of key phrases and syntax structures identified in the literature as significant.¹⁰¹ As illustrated by Table 2.2, this includes four central summary dimensions as functions of specific data associated with 93 different psychological cues that are recorded by frequency per case brief. In effect, the summary distinguishes rhetorical strategies by perception (consisting of both emotional tone and authenticity), reason (analytic), and reputation (clout).¹⁰²

Table 2.2. Linguistic Inquiry and Word Count (LIWC)
Summary Dimensions

Analytic

Clout

Authentic

Emotional Tone

For labels, Supreme Court case results (“Opinion”) are integer encoded (affirmed = 0; vacated / reversed = 1; partially affirmed / vacated / reversed = 2; petition denied / dismissed = 3). The procedural stance of the case (“Procedural”), i.e., if the case is remanded or not, is one-hot encoded (not remanded = 0; remanded = 1).¹⁰³

¹⁰⁰ See, e.g., Di Xue et al., *Deep Learning-Based Personality Recognition from Text Posts of Online Social Networks*, 48 APPLIED INTEL. 4232 (2018) (providing an analysis of deep-learning personality recognition on text mined social media posts). For a generic framework of analyzing text mined documents, see Sneha Sukheja et al., *Sentiment Analysis Using Deep Learning – A Survey*, 2020 INT’L CONF. ON COMPUT. SCI., ENG’G & APPLICATIONS (ICCSEA), Jul. 2020.

¹⁰¹ See Tausczik & Pennebaker, *supra* note 51. “The 80 language categories in LIWC have been linked in hundreds of studies to interesting psychological processes.” *Id.* at 30.

¹⁰² See Tausczik & Pennebaker, *supra* note 51, at 30–31 (perception); Roger McHaney et al., *Using LIWC to Choose Simulation Approaches: A Feasibility Study*, 111 DECISION SUPPORT SYS., 2018 (reason and reputation); John Sell & Ingrid G. Farreras, *LIWC-ing at a Century of Introductory College Textbooks: Have the Sentiments Changed?*, 118 PROCEDIA COMPUT. SCI. 108 (2017) (reputation).

¹⁰³ See, e.g., Michael A. Livermore et al., *The Supreme Court and the Judicial Genre*, 59 ARIZ. L. REV. 837, 856 (2017) (providing an example of one-hot encoding case results); Elliott Ash et al., *Precedent vs. Politics? Case Similarity Predicts Supreme Court Decisions Better than Ideology*, SOC. SCI. RSCH. NETWORK, June 25, 2017, at 5 (providing an example of a study using one-hot coding citations).

VII. Data Collection

This study reviews a population of government petitions made to the Supreme Court during the Roberts Court that are matched to Supreme Court opinions.

First, a python webscraper extracts government petitions from the Justice Department website and converts the files to portable document format (PDF). The files are then run through LIWC to produce psychological data on a csv file, with each case denoted by a docket number.

Second, a python webscraper extracts Supreme Court opinions from the Supreme Court website. These opinions are scraped for Supreme Court opinion verdicts and procedural stance, which are recorded in a csv file and denoted by a docket number.

Third, data from government petitions and Supreme Court opinions are merged into one csv file and matched based on docket number.

Fourth, the data is stress-tested manually by research assistants. These assistants search each case by name and docket number.

VIII. Analysis

Our neural network models the transformed data to predict Supreme Court opinion verdicts (hereinafter “Opinion Model”) and procedural stance (hereinafter “Procedural Model”). We used the Tensorflow python environment to simulate models.¹⁰⁴

First, parameters were tuned for optimal area under the curve (AUC) and then fortified against overfitting. LIWC variables were sorted as features, with “result” and “remanded” assigned as labels. “Docket number” and “result text,” both of which were only meant for matching and reference by research staff, were removed during preprocessing. To tune, we simply used the trial-and-error method.¹⁰⁵

¹⁰⁴ We would like to thank Blockchain Web Services (BWS) for assistance with tuning. BLOCKCHAIN WEB SERVICES, <https://bws.xyz/> (last visited Apr. 5, 2023) [<https://perma.cc/HM8A-DD6H>].

¹⁰⁵ See PS Janardhanan, *Project Repositories for Machine Learning with TensorFlow*, 171 *PROCEDIA COMPUT. SCI.* 188, 191 (2020) (“We may not know the best combination of values for hyper-parameters in advance for a given problem. We may use rules of thumb, copy values used on other problems, or search for the best value by trial and error.”). See also HISHAM EL-AMIR & MAHMOUD HAMDY, *DEEP LEARNING PIPELINE: BUILDING A DEEP LEARNING MODEL WITH TENSORFLOW* 57–84 (2020).

Second, after defining features and labels, the model passed the data into float. The data was then split into training and test sets (test proportion: 0.20). Data used for training was then passed into an array to control for class frequency bias, as reported by table 3.1.

Opinion Model			Procedural Model		
Class	Frequency	Weight	Class	Frequency	Weight
Affirm	293	2.3422	Not Remanded	2110	0.6505
Reverse / Vacate	661	1.0382	Remanded	635	2.1614
Partially Reverse / Vacate / Affirm	154	4.4561			
Petition Denied / Dismissed / Other	1637	0.4192			

Using a sequential function, hidden layers were added using a Rectified Linear Unit (ReLU) activation function ($f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$)¹⁰⁶. For each layer, we also introduced a dropout regulator to control for overfitting.¹⁰⁷

Module: tf, TENSORFLOW (Mar. 24, 2023), https://www.tensorflow.org/api_docs/python/tf [<https://perma.cc/P2MZ-BMQ2>] [hereinafter *Tensorflow 2.0*]. See Fatih Ertam & Galip Aydin, *Data Classification with Deep Learning Using Tensorflow*, 2017 INT’L CONF. ON COMPUT. SCI. & ENG’G (UBMK) 755, 756 (2017); cf. *id.* at 757 (demonstrating that ReLU is more effective than competing functions, such as TanH, or Sigmoid).

¹⁰⁷ *Tensorflow 2.0*. See B. R. KAVITHA ET AL., *Deep Learning for Character Recognition*, in ADVANCED DEEP LEARNING FOR ENGINEERS AND SCIENTISTS: A PRACTICAL APPROACH 61, 76 (Kolla Bhanu Prakash et al. eds., 2021) (“[T]o avoid the overfitting of the model a popular technique called Dropout is used, which drops some of the neurons to be inactive, thereby allowing the network to traverse through different architectures for every epoch.”).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

Third, we selected an appropriate activation function for each model. For the Opinion Model, we passed a softmax activation function to fit for a multiclass problem:

$$s(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_a}}$$

Where $s(x_i)$ is a function of e to the power of each sample number, divided by the sum of all the exponentials.¹⁰⁸ For the Procedural model, we passed a sigmoid activation function to fit for a binary problem:

$$s(x) = \frac{1}{1 + e^{-x}}$$

Simply put and transformed, $s(x_i)$ is a function of e^x divided by the sum of e^x and 1. Both functions produce an output between zero (0) and (1), which translates to a probability.¹⁰⁹ Each probability for either model is then expressed as a coefficient matched to each label class.

Fourth, we used Adam for the optimizer function to optimize for an output with a high accuracy.¹¹⁰

Fifth, we assigned each model a loss function to measure learning. The Opinion Model, being a multiclass (single level categorization) problem, was assigned categorical crossentropy.¹¹¹ The Procedural Model, being a binary problem, was assigned binary crossentropy.¹¹² Final tuning is reported in table 3.2.

¹⁰⁸ *Tensorflow 2.0*. See Siddharth Sharma et al., *Activation Functions in Neural Networks*, 4 INT’L J. ENG’G APPLIED SCIS. & TECH. 310, 314 (2020); GIANCARLO ZACCONE ET AL., *DEEP LEARNING WITH TENSORFLOW* 112 (2017) (explaining that softmax is preferable for a multi-class problem); FABIO NELLI, *PYTHON DATA ANALYTICS: WITH PANDAS, NUMPY, AND MATPLOTLIB* 377 (2d ed. 2018). *But cf.* Reid Pryzant, *Evaluating Tensorflow*, DEP’T COMPUT. SCI. STAN. U., at 5–6 (explaining that, with a webscraped commercial dataset, Tensorflow’s softmax function can struggle to identify trends, and hypothesizing that there may be “flaws in the Tensorflow source code” as a result of “the fickle nature of [such] complex systems”).

¹⁰⁹ *Tensorflow 2.0*. See Ertam & Aydin, *supra* note 106, at 757; ZACCONE ET AL., *supra* note 108, at 14–15, 77 (explaining that the sigmoid function is most appropriate for a binary). *But cf.* Pryzant, *supra* note 108, at 6 (explaining that a dataset created using the sigmoid function turned out to be “rubbish”).

¹¹⁰ *Tensorflow 2.0*. See PRAMOD SINGH & AVINASH MANURE, *LEARN TENSORFLOW 2.0: IMPLEMENT MACHINE LEARNING AND DEEP LEARNING MODELS WITH PYTHON* 53–74 (2020).

¹¹¹ *Tensorflow 2.0*. See SILAPARASETTY, *supra* note 111, at 105–06, 342.

¹¹² *Tensorflow 2.0*. See SILAPARASETTY, *supra* note 111, at 105–06, 342.

Table 3.2. Tuned Hyperparameters and Neutral Network Layers for Opinion and Remand Models

	Opinion Model		Procedural Model	
Layer	Filters	Parameters	Filters	Parameters
Input	1224	116280	2400	228000
Hidden	862	1055950	1224	2938824
Hidden	424	365912	624	764400
Hidden	124	52700	124	77500
Hidden	16	2000	16	2000
Batch Normalization	16	64	16	64
Output	4	64	2	34
Dropout	0.5, 0.5, 0.5		0.25, 0.25, 0.2	
Epochs	30		50	
Total Trainable Parameters	1,592,974		4,010,790	

Sixth, we used several metrics to analyze the strength of our models. For generalized accuracy, we used AUC for both models,¹¹³ which is superior to accuracy due to increased sensitivity as well as independence from class bias and decision thresholds.¹¹⁴ Moreover, to illustrate practical and systemic accuracy,

¹¹³ *Tensorflow 2.0*. See André Carrington et al., *Deep ROC Analysis and AUC as Balanced Average Accuracy, for Improved Classifier Selection, Audit and Explanation*, 45 IEEE TRANSACTIONS ON PATTERN ANALYSIS & MACH. INTEL. 329, 330 (2023) (demonstrating that AUC can effectively “evaluate all decision thresholds”). *But cf. id.* at 330 (demonstrating that measuring all decisions is not necessarily good, as it may also include undesirable or “unrealistic or undesirable ones”). Because all possible Supreme Court outcomes are desirable to know, we exclude this possibility.

¹¹⁴ See Charles X. Ling et al., *AUC: A Better Measure than Accuracy in Comparing Learning Algorithms*, in *ADVANCES IN ARTIFICIAL INTELLIGENCE* 329, 331 (Yang Xiang & Brahim Chaib-draa eds., 2003) (“AUC exhibits several desirable properties compared to accuracy. For example,

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

models were assigned a Top K Categorical Accuracy (Opinion: k=3; Procedural, k=1).¹¹⁵ For the Procedural model, we reported precision and recall.¹¹⁶ For the Opinion model, we then reported Sensitivity at Specificity (0.5) and Specificity at Sensitivity (0.5).¹¹⁷ We differentiated metric choices for each model for three reasons: first, because precision and specificity differ in meaning (precision =

$$\frac{\text{true positives}}{\text{true positives} + \text{false positives}};$$

$$\text{specificity} = \frac{\text{true negatives}}{\text{true negatives} + \text{false positive}}), \text{ each must be applied}$$

contextually.¹¹⁸ Specificity is better at predicting true negatives.¹¹⁹ Because our multiclass model needed to be optimized for robustness,¹²⁰ specificity fits better to the Opinion model. Second, because keras passes precision and recall as booleans, neither metric supports multiclass problems.¹²¹ For these reasons, the Opinion Model reports sensitivity and specificity, while the Procedural Model uses precision and recall.

AUC has increased sensitivity in Analysis of Variance (ANOVA) tests, is independent to the decision threshold, and is invariant to *a priori* class probability distributions ... We show, empirically and formally, that AUC is indeed a statistically consistent and more discriminating measure than accuracy.”).

¹¹⁵ See, e.g., DINO PEDRESCHI ET AL., *Measuring Discrimination in Socially-Sensitive Decision Records*, in PROCEEDINGS OF THE 2009 SIAM INTERNATIONAL CONFERENCE ON DATA MINING 581, 591 (Chid Apte et al. eds., 2009) (showing the use of top-k in measuring discrimination).

¹¹⁶ SILAPARASETTY, *supra* note 111, at 100; NARESH JASOTANI, *ADOPTING TENSORFLOW FOR REAL-WORLD AI: A PRACTICAL APPROACH - TENSORFLOW V2.2* 41, 124 (2020); See generally ANTONIO GULLI & SUJIT PAL, *DEEP LEARNING WITH KERAS: IMPLEMENT NEURAL NETWORKS WITH KERAS ON THEANO AND TENSORFLOW* (2017).

¹¹⁷ *Tf.keras.metrics.SpecificityAtSensitivity: Tensorflow core v2.8.0*, TENSORFLOW, https://www.tensorflow.org/api_docs/python/tf/keras/metrics/SpecificityAtSensitivity [<https://perma.cc/KA9X-6HHD>] (last visited Apr 13, 2022); See, e.g., Arwa Mohammed Taqi et al., *The Impact of Multi-Optimizers and Data Augmentation on Tensorflow Convolutional Neural Network Performance*, 2018 IEEE CONFERENCE ON MULTIMEDIA INFORMATION PROCESSING & RETRIEVAL (MIPR) (2018).

¹¹⁸ See, e.g., Stefano Cresci et al., *DNA-inspired online behavioral modeling and its application to spambot detection*, 31 IEEE INTELLIGENT SYSTEMS 63 (2016) (demonstrating that specificity can be higher than precision for spambots).

¹¹⁹ Rajul Parikh et al., *Understanding and Using Sensitivity, Specificity and Predictive Values*, 56 INDIAN J. OF OPHTHALMOLOGY 45, 45–50 (2008); See also Karen Steward, *Sensitivity vs Specificity Analysis*, TECHNOLOGY SYSTEMS (Apr 16, 2022), <https://www.technologynetworks.com/analysis/articles/sensitivity-vs-specificity-318222> [<https://perma.cc/EG56-ZTEF>].

¹²⁰ See, e.g., Shaikat Hayat et al., *A Deep Learning Framework Using Convolutional Neural Network for Multi-Class Object Recognition*, 2018 IEEE INT’L CONFERENCE ON IMAGE, VISION & COMPUTING (ICIVC) (2018) (showing that convolutional networks can be optimized for robustness using regulators).

¹²¹ *Tf.keras.metrics.precision: Tensorflow core v2.8.0*, TENSORFLOW, https://www.tensorflow.org/api_docs/python/tf/keras/metrics/Precision [<https://perma.cc/G5LR-X27T>] (last visited Apr 13, 2022).

IX. Results

As reported in table 4.1 and 4.2, the mean and standard deviation for each psychological indicator is sorted by label class.

Table 4.1. Opinion Frequency Statistics
(Opinion, $N = 2745$)

	Affirm		Reverse / Vacate		Partially Affirm / Vacate / Reverse		Petition Denied / Dismissed / Other	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Analytic	96.64	1.22	96.73	1.40	96.79	1.24	96.70	1.18
Clout	44.16	4.71	45.42	5.16	45.46	5.77	44.57	4.82
Authentic	10.35	5.14	10.46	5.47	10.43	4.18	9.42	4.72
Tone	31.37	17.83	30.28	16.26	33.37	14.94	29.29	15.62
Frequency	293		661		154		1637	

Table 4.2. Procedural Frequency Statistics
(Procedural, $N = 2745$)

	Not Remanded		Remanded	
	Mean	Std.	Mean	Std.
Analytic	96.69	1.20	96.74	1.38
Clout	44.60	4.87	45.38	5.23
Authentic	9.70	4.91	10.26	5.07
Tone	29.94	15.89	30.11	16.42
Frequency	2110		635	

X. Model Performance

The Opinion and Procedural models were trained under the hyperparameters, as recorded in table 3.2. Table 5.1 reports the Opinion model prediction outputs.

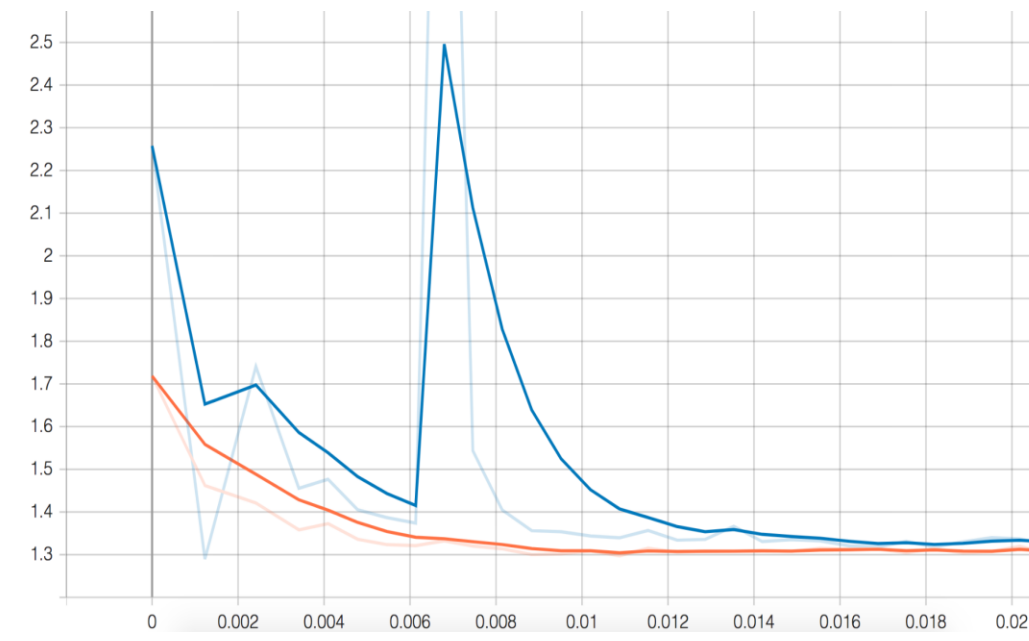
Table 5.1. Opinion Prediction Outputs

Metric	Opinion Model
AUC	.8087
Top K Categorical Accuracy	.9144
Sensitivity	.8725
Specificity	.9211

For predicting the outcome of a case, the returns demonstrated the model operated more accurately than both randomization and the traditional models (AUC = .8087). Furthermore, the Top K Categorical Accuracy score suggested that for every three predictions, there was over a 90% chance of at least one correct guess. The high scores above the AUC suggest that the predictive model functions strongly in the aggregate. Unsurprisingly, the multiclass nature of the Opinion model reflected a specificity score higher than sensitivity. In effect, this means that the Opinion model is more efficient at sorting false positives than false negatives.

Next, Figure 3.1 illustrates the close convergence of training and validation data, suggesting the Opinion model can be generalized. Because the relatively small number of Supreme Court cases created systemic overfitting, a slightly underfit model was selected to produce more conservative, robust results. Figure 3.1 was recorded using a smoothed loss function (y-axis: loss; x-axis: epochs). Using tensorboard, we smoothed the loss function at 0.6.

Figure 3.1. Opinion Loss Model



The orange line represents the training and the blue validation. Out of the trained models, we selected for a more conservative model of slight underfit instead of slight overfitting, of which was common due to the complexity of the model and relatively small amount of data.

Table 5.2 Reports the Procedural Model prediction outputs.

Table 5.2. Procedural Prediction Outputs

Metric	Opinion Model
AUC	.7616
Top K Categorical Accuracy	.7413
Precision	.7491
Recall	.7231

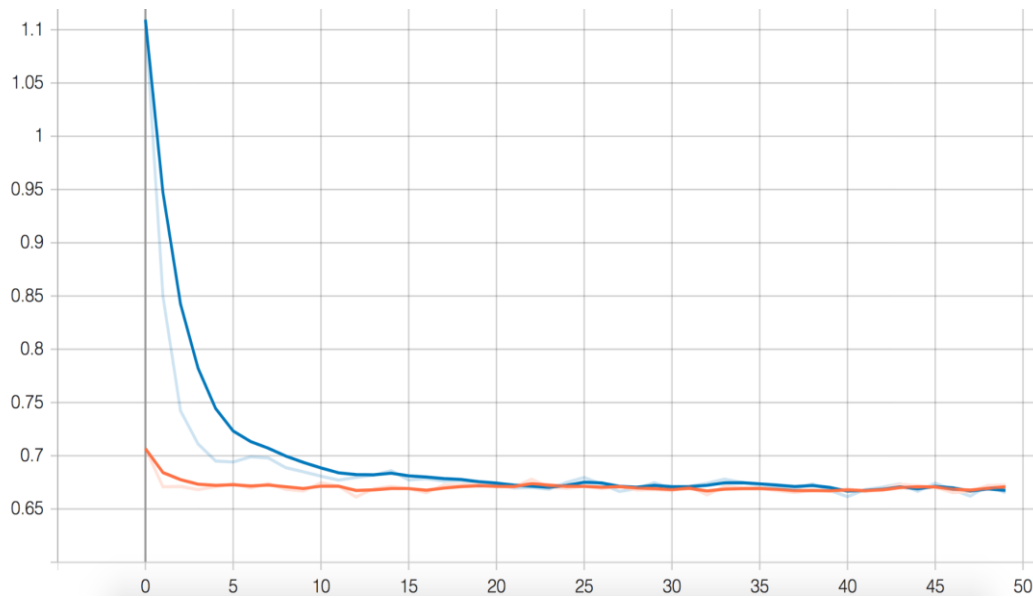
For predicting the final procedural stance of a case, the returns demonstrated the model operated more accurately than randomization (AUC = .7616). Furthermore, the Top K Categorical Accuracy suggested that for every

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

single prediction, there was almost a 75% chance of a correct guess. A lower Top K Categorical Accuracy score than AUC indicates that the model performs well across class labels but is effected by class bias, which affects the practical accuracy of field testing. The precision and recall scores relatively near to the AUC suggest that the model functions well predicting for positive classes.

Finally, Figure 3.2 illustrates the close convergence of training and validation data, suggesting the Procedural model can be generalized. Figure 3.2 was recorded using a smoothed loss function (y-axis: loss; x-axis: epochs). Using tensorboard, we smoothed the loss function at 0.6.

Figure 3.2. Procedural Loss Model



The orange line represents the training and the blue validation.

XI. Case Example Predictions

Both the Opinion and Procedural models were saved and then used to predict the final outcomes of current, unresolved Supreme court cases. These cases were selected as recorded under Table 2.1. Table 6.1 reports the label class and probability coefficient for each model. The coefficient is then translated into a label class prediction.

Table 6.1. Case Example Predictions

	Opinion Model		Procedural Model	
Case	Label Class	Probability	Label Class	Probability
<i>Carson v. Makin, 20-1088.</i>	Affirm	.2815	Not Remanded	.4249
	Reverse / Vacate	.2970	Remanded	.5556
	Partially Reverse / Vacate / Affirm	.2731		
	Petition Denied / Dismissed / Other	.1485		
Prediction	Reverse / Vacate		Remanded	
<i>Dobbs v. Jackson Women’s Health Organization, 19-1392.</i>	Affirm	.2512	Not Remanded	.4773
	Reverse / Vacate	.2725	Remanded	.5080
	Partially Reverse / Vacate / Affirm	.2561		
	Petition Denied / Dismissed / Other	.2202		
Prediction	Reverse / Vacate		Remanded	

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

<i>Federal Bureau of Investigation v. Fazaga, 20-828.</i>	Affirm	.2872	Not Remanded	.4109
	Reverse / Vacate	.3012	Remanded	.5684
	Partially Reverse / Vacate / Affirm	.2757		
	Petition Denied / Dismissed / Other	.1361		
Prediction	Reverse / Vacate		Remanded	
<i>George v. McDonough, 21-234.</i>	Affirm	.2218	Not Remanded	.5221
	Reverse / Vacate	.2463	Remanded	.4675
	Partially Reverse / Vacate / Affirm	.2356		
	Petition Denied / Dismissed / Other	.2964		
Prediction	Petition Denied / Dismissed / Other		Not Remanded	
<i>Students for Fair Admissions v. President and Fellows of Harvard College, 20-1199.</i>				

	Affirm	.2232	Not Remanded	.5224
	Reverse / Vacate	.2475	Remanded	.4673
	Partially Reverse / Vacate / Affirm	.2366		
	Petition Denied / Dismissed / Other	.2927 ¹²²		
Prediction	Reverse / Vacate		Not Remanded	
<i>New York State Rifle & Pistol Association Inc. v. Bruen</i> , 20-843.	Affirm	.2913	Not Remanded	.4032
	Reverse / Vacate	.3041	Remanded	.5755
	Partially Reverse / Vacate / Affirm	.2774		
	Petition Denied / Dismissed / Other	.1272		
Prediction	Reverse / Vacate		Remanded	
<i>Shurtleff v. City of Boston</i> , 20-1800.	Affirm	.2875	Not Remanded	.4130

¹²² See *Students for Fair Admissions Inc. v. President & Fellows of Harvard College*, 980 F.3d 157 (1st Cir. 2020) (at the time of this prediction the case was already being heard for oral arguments, so one can dismiss predictions of cert being denied or dismissal).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

	Reverse / Vacate	.3014	Remanded	.5665
	Partially Reverse / Vacate / Affirm	.2758		
	Petition Denied / Dismissed / Other	.1353		
Prediction	Reverse / Vacate		Remanded	
<i>United States v. Tsarnaev, 20-443.</i>	Affirm	.2215	Not Remanded	.5247
	Reverse / Vacate	.2459	Remanded	.4651
	Partially Reverse / Vacate / Affirm	.2353		
	Petition Denied / Dismissed / Other	.2973		
Prediction	Petition Denied / Dismissed / Other		Not Remanded	

XII. Discussion

To meaningfully understand the efficiency of SCOTUS_AI, one must compare against both a given null model and similar studies. If we exclude denied petitions, a strong, biased null model would result in 63% accuracy and always guess “reverse,” as illustrated by Table 4.1.¹²³ SCOTUS_AI, in every metric, outcompetes this null model. Moreover, because the Top-K value exceeds the AUC value, SCOTUS_AI is robust against AUC cheating with unrealistic classes.

¹²³ Katz, Bommarito, & Blackman, *supra* note 95, at 9 (“...the recent history of the Court over the last 35 terms: 57% of Justice votes and 63% of case outcomes have been Reverse”); *See also* Aaron Russell Kaufman et al., *Improving Supreme Court forecasting using Boosted Decision Trees*, 27 POL. ANALYSIS 381, 381–87 (2019) (explaining that guessing petitioner, for most of the Court’s history, would result in a correct prediction more than 67% of the time).

The results, thus, are trustworthy in aggregate. However, as noted by some scholars, such a null model, while academically informative in demonstrating the model is better than random guessing, fails to offer practical insight into Supreme Court behavior.¹²⁴ Because the benefits of machine learning are best illustrated by comparative strength, one must compare and contrast with competing models.

Before specifically examining studies, a few generalizable findings can be immediately made for both the Opinion and Procedural models. First, SCOTUS_AI's prediction outputs, in general, are more accurate than comparable studies. Second, because SCOTUS_AI uses AUC, it avoids many of the problems associated with accuracy; namely, the impotence such models tend to show with specific classes.¹²⁵ Moreover, because many of the studies rely on a binary label classification system, SCOTUS_AI can identify a larger range of possibilities at a more accurate rate. Finally, despite class bias, both the Opinion and Procedural models reflected strong subsidiary metrics, such as precision, recall, and sensitivity, suggesting that SCOTUS_AI can be used in practice without significant accounts of cheating. Finally, because the SCOTUS_AI algorithm's is rather new in the academic field, it is important to proceed under the assumption that traditional modeling can be compared; indeed, it may be that SCOTUS_AI is more efficient simply because of its mathematical structure rather than data, which would suggest that the other models are more competitive than they may seem.

Comparing the features and specific outcomes of selected comparable models offers insight to the particular strength of sentiment analysis over institutionalism and traditional psychology paradigms. The most accurate comparable model, *Ruger et al.*, is primarily institutionalist.¹²⁶ The *Ruger* model, 75% accurate,¹²⁷ suffers from three primary deficiencies. First, on face, the model is roughly 5% less accurate than SCOTUS_AI. Second, this differential is amplified due to the lack of supplemental metrics. This makes examining performance, such as the presence of false positives, difficult. Third, the *Ruger* model simply looks at "Not Reverse" and "Reverse," a much smaller range of possibilities compared to SCOTUS_AI. For this reason, the predictions made by the *Ruger* model are not as fruitful as those made by SCOTUS_AI. This does not mean, however, that the *Ruger* model is inconsistent with SCOTUS_AI. Indeed, as previously noted, certain psychological sentiments may be related to political dispositions.¹²⁸ As a result, it is possible that the SCOTUS_AI model simply serves as a more effective mediator of distinguishing preference for political ideology than a largely subjective lower court ideological disposition.

¹²⁴ Katz, Bommarito, & Blackman, *supra* note 95, at 8; Ruger et al., *supra* note 24, at 1161.

¹²⁵ Yang Xiang et al., *supra* note 114, 331.

¹²⁶ Ruger et al., *supra* note 24, at 1161.

¹²⁷ *Id.*

¹²⁸ *Id.*

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

A second comparable model, *Katz et al.*, correctly predicts case outcomes about 70% of the time using institutionalist features such as the reason for granting cert and lower court disposition.¹²⁹ Similar to the *Ruger* model, the *Katz* model is less accurate than SCOTUS_AI and is unable to predict for a wide range of possibilities. In terms of precision, the *Katz* model and SCOTUS_AI are largely not comparable, largely because the Keras prediction function only works with binary classes.¹³⁰ SCOTUS_AI's sensitivity, however, does outcompete *Katz*'s recall, suggesting that SCOTUS_AI controls better for false negatives. In context, this means that when an outcome is not predicted for, such as the Court not "reversing," SCOTUS_AI is more accurate.

A third comparable model, *Dietrich*, correctly predicts 63% of cases, focusing on the non-verbal signaling of judges during oral arguments, such as pitch.¹³¹ *Dietrich*'s modeling of a judge's psychology is interestingly less accurate than SCOTUS_AI and aforementioned institutionalist models. The strength of *Dietrich*'s logistic regression compared to SCOTUS_AI is in terms of theoretical application: while SCOTUS_AI optimizes for fitted accuracy, *Dietrich* can more strongly understand how each sentiment, such as "pleasant words," weighs the algorithm. While SCOTUS_AI is significantly more accurate, *Dietrich*'s model provides theoretical strength for the relationship between psychology and the rules.

Katz and *Ruger* primarily utilized institutionalist features. *Dietrich*, when using sentiment analysis, primarily focused on the individual judges during oral hearings, rather than the larger, contextual setting offered by full briefings. Both, however, fail to compete against SCOTUS_AI, which offers several theoretical implications. First, the evidence suggests that the underlying psychological sentiment reflected on a case may better explain outcomes and procedural stance than the traditional expert analysis institutionalists propose.¹³² Functionally, LIWC crudely summarizes psychological relation through word frequency summarization. In practice, this may mean that seemingly unemotional briefs primarily characterized by legal norms, terms, and rules are actually substitutes for other, underlying subconscious biases.¹³³ Overarching legal norms, such as *stare decisis*, reflect the inherent path dependence built into legal outcomes.

¹²⁹ Katz, Bommarito, & Blackman, *supra* note 95, at 8.

¹³⁰ TENSORFLOW, *supra* note 121.

¹³¹ Bryce J. Dietrich, Ryan D. Enos & Maya Sen, *Emotional arousal predicts voting on the U.S. Supreme Court*, 27 POLITICAL ANALYSIS 1, 1–18 (2018).

¹³² *Id.*

¹³³ See Ruger et al., *supra* note 24, at 1161 ("Neither of our methods of prediction is designed to test a pure theory of what motivates the Justices."). Because SCOTUS_AI is only predictive and not suggestive, it is unclear whether the level of emotion increases or decreases the chances of success, or in what context.

Because this path dependence is interpreted by judicial actors with bounded rationality, SCOTUS_AI's behavior suggests that cases can be emotionally framed through seemingly unemotional means: syntax, communal reference through case citations, the signaling of certain ideas or assumptions through legal principles, may in their emotional meaning rather than logical application best explain for case outcomes. While it is alternatively possible that the briefs are mere substitutes for predetermined judge preference, one would expect political ideology to explain this, which both *Katz* and *Ruger* struggle to do. And again, while one could contend that political ideology cannot be easily summarized as *Katz* and *Ruger* attempt to do, this would only strengthen the assumption behind SCOTUS_AI that ideology is best understood as a mediator for deeper, less explicit desires. In practice, this means that it may be possible lawyers can improve their chances of winning a case by psychologically priming, rather than only logical coherence, of their arguments.¹³⁴

Second, even though the psychological framing of a case may intersect and mediate some of the impact of *stare decisis* on case outcomes, SCOTUS_AI's relative effective performance suggests that sentiment may have a wider role than institutional mediation suggests. It may, for example, be that judicial actors can actually be persuaded, or at least distracted, from broader legal claims when primed with certain emotional signals. Moreover, while SCOTUS_AI is not directly fed externalities, it is possible that externalities, such as public pressure, are mediated by phrases in each brief. As was prior noted, for instance, cases on important societal issues, such as gay marriage and abortion, often contain inflammatory language and contexts that modify appraisal and emphasis on elements outside of the law.¹³⁵ Third, while it may be tempting to equivocate ideological disposition with sentiment, the model results confound this expectation. Both the *Ruger* and *Katz* models factored in ideology in multiple ways, and neither approached SCOTUS_AI's accuracy. In effect, either sentiment is a better measure than subjective determinations of ideology, or sentiment is more than only ideology. Nor is sentiment as easily accessible as party disposition towards a case; the *Dietrich* model almost exclusively examines the leaning of judges in oral arguments and still lacks the accuracy provided by a text-mined analysis conducted by SCOTUS_AI. These implications suggest that either the rules alone or preexisting political affiliation do not sufficiently mediate the entire effect of emotivism, supporting a view that subconscious drives are often complex and multifaceted. Furthermore, SCOTUS_AI with its generic dictionary of

¹³⁴ It is important to note this observation does not mean that logical coherence is irrelevant, only that it does not fully mediate emotion. See Black et al., *supra* note 70, at 26 (“[A]ttorneys should not make overt emotional appeals...”).

¹³⁵ See, e.g., *id.* at 25 (“[W]hen reading, judges may anticipate written opinions and how the arguments made in the briefs will translate into policy. Previous work demonstrates that this is not strictly a mental exercise, but rather, that justices actually ‘borrow’ the language in parties’ briefs for use in final opinions and that their proclivity to do so varies at the individual level”).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

psychological phrases, offers support for the psycholinguistic framework: cognition and the subconscious elements that create a basis for it can serve as an independent but universally accessible predictor of human behavior.

While theory is important, a final practical metric for analyzing the efficiency of a model is to deploy it into the field. By predicting future cases and offering implications, this will allow future studies to retrospectively analyze the model's efficiency in a real world setting. As Table 6.1 illustrates, SCOTUS_AI has predicted a number of case outcomes, all of which must then be placed into context. Cases that were decided during the writing of this article are noted.

For *Carson*, 20-1088, the model predicts that the lower court's ruling will be reversed and or vacated, and remanded for further proceedings. In *Carson*, petitioners alleged that a Maine state statute that denied high school students of tuition assistance if a school was deemed "sectarian" violated the First Amendment Free Exercise Clause and the Fourteenth Amendment Equal Protection Clause.¹³⁶ The lower court upheld the state law.¹³⁷ SCOTUS_AI believes that the Supreme Court will reverse and or vacate the opinion of the lower court, likely meaning that the legal rule used to uphold the Maine state statute will be written or reinterpreted. SCOTUS_AI then predicts that the Supreme Court will remand the case back to a lower court, likely with a new rule requiring a factual finding. In doing so, this prediction supports the general trend of the literature that the Court will expand the Free Exercise Clause to more extensively protect religious schools.¹³⁸

For *Dobbs v. Jackson Women's Health Organization*, 19-1392, the model predicts that the lower court ruling will be reversed or vacated, with the case remanded for further proceedings. In *Dobbs*, the petitioner contended the appellate court erred by holding a Mississippi statute that bans pre-viability abortion as unconstitutional.¹³⁹ SCOTUS_AI predicts that the Supreme Court will reverse, likely implying a challenge, or at least reconciliation, to *Roe v. Wade* and *Casey v. Planned Parenthood*.¹⁴⁰ SCOTUS_AI then forecasts that the case will be remanded to a lower court, likely with a new rule requiring a factual finding. In

¹³⁶ *Carson as next friend of O.C. v. Makin*, 979 F.3d 21, 26 (1st Cir. 2020).

¹³⁷ *Id.* at 49.

¹³⁸ See Amy Howe, *Looking ahead: A Post-COVID Return - And a Shift to the Right?*, 2020 CATO SUP. CT. REV. 263 (2020-2021) (explaining that the Court in *Carson* is addressing an unanswered question from *Espinoza v. Montana Dept. of Revenue*, which if found for petitioners would deem unlawful the exclusion of families from tuition-assistance when the aid is used for religious instruction in school is unconstitutional).

¹³⁹ See Brief for Petitioner at 5, *Dobbs v. Jackson Women's Health Org.*, 141 S. Ct. 2619 (2021) (No. 19-1392).

¹⁴⁰ See Jeffrey Hannan, *Dobbs v. Jackson Women's Health Organization and the Likely End of the Roe v. Wade Era*, 17 DUKE J. CONST. L. & PUB. POL'Y 281, 302 (2022) (explaining that *Roe* and *Casey* are unlikely to survive a *Dobbs* decision for the petitioner).

doing so, this prediction provides some evidence that the abortion rights established in case precedent will be further reduced.¹⁴¹

For *Federal Bureau of Investigations v. Fazaga*, 20-828, the model predicts that the lower court ruling will be reversed or vacated, with the case remanded for further proceedings.¹⁴² In *Fazaga*, the petitioner contended that the Foreign Intelligence Surveillance Act does not trump state-secrets privilege and that the Ninth Circuit Court of Appeals erred in its decision.¹⁴³ SCOTUS_AI predicts the Supreme Court will reverse, indicating a strengthened deference to the executive branch in surveillance operations.¹⁴⁴

For *George v. McDonough*, 21-234, the model predicts that the Supreme Court will either deny cert or be dismissed on other grounds. However, because the case has already had arguments heard, this possibility is unlikely. The second most probable event coefficient is that the Supreme Court will reverse or vacate, with the case not being remanded. In *McDonough*, petitioner alleged the lower court erred by barring a veteran from challenging the Veteran Administration's decision when there is a "clear and unmistakable error."¹⁴⁵ SCOTUS_AI predicts the Court will reverse, indicating that if the petitioner's argument prevails, the Court may hold that an agency interpretation that is at odds with the plain meaning of the law cannot be retrospectively applied to veteran claimants.¹⁴⁶

For *Students for Fair Admissions v. President and Fellows of Harvard College*, 20-1199, the model predicts that the Supreme Court will either deny cert or be dismissed on other grounds. However, because the case has already had arguments heard, this possibility is unlikely. The second most probable event coefficient is that the Supreme Court will reverse or vacate, with the case not being remanded. In *Students for Fair Admissions*, the petitioner contended that a lower court erred by permitting Harvard College to use race as a factor in college admissions, at odds with the Fourteenth Amendment's Equal Protection Clause.¹⁴⁷ SCOTUS_AI predicts the Court will reverse, indicating a challenge to the *Grutter*

¹⁴¹ *Id.* ("Dobbs likely signals the end of Roe and Casey's hold over all prohibitions on pre-viability abortions.").

¹⁴² *Federal Bureau of Investigation v. Fazaga*, 142 S.Ct. 1051 (2022) (This case was decided during the writing of this article).

¹⁴³ Brief for Petitioner at 17-8, *Federal Bureau of Investigations v. Fazaga*, 142 S.Ct. 1051 (No. 20-828) (2022).

¹⁴⁴ See Rebecca Reeves, *F.B.I. v. Fazaga: The Secret of the State-Secrets Privilege*, 17 DUKE J. CONST. L. & PUB. POL'Y 267, 278 (2022) ("To allow the executive to prevent FISA from being properly applied to this case would be to privilege [the executive] branch over the others.").

¹⁴⁵ Brief for Petitioner at 2-3, *George v. McDonough*, 991 F. 3d. 1227 (2021) (No. 21-234).

¹⁴⁶ See *George v. McDonough*, 991 F. 3d. 1227, 1238 (Fed. Cir. 2021).

¹⁴⁷ Petition for Writ of Certiorari at 42-4, *Students for Fair Admissions, Inc. v. President & Fellows of Harvard College*, 980 F. 3d. 187 (2021) (No. 20-1199).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

v. Bollinger precedent and potentially affirmative action in general.¹⁴⁸

Interestingly, the algorithm also predicts the case will not be remanded, suggesting that the factual question of whether Harvard did engage in discrimination will not be relevant to the outcome. This opens the possibility for a more expansive prohibition on affirmative action that would not require further inspection by a lower court and only require an admission of any racial benefit in the admission process.¹⁴⁹

For *New York State Rifle & Pistol Association Inc. v. Bruen*, 20-843, the model predicts the Supreme Court will reverse and or vacate, with the case being remanded. In *New York State Rifle*, petitioner alleged the lower court erred by holding lawful a New York statute that prohibited citizens from carrying a firearm outside their home without a license showing “proper cause.”¹⁵⁰ SCOTUS_AI predicts the Court will reverse, potentially expanding the *Heller* precedent to prevent state restrictions on carrying weapons outside the home for self-defense.¹⁵¹ The case being remanded also suggests that the lower courts may need to do further factual investigation into whether the New York law meets the new rule established by the Supreme Court.

For *Shurtleff v. City of Boston*, 20-1800, the model predicts the Supreme Court will reverse and or vacate, with the case being remanded. In *Shurtleff*, petitioner alleged that a Boston municipal policy that approved the flying of hundreds of flags, but denied flying a flag for a private religious organization violated the First Amendment forum doctrine.¹⁵² Second, petitioner argued that lower court erred by designating a flagpole a public forum open to all applicants as “government speech.”¹⁵³ SCOTUS_AI predicts the Court will reverse, with scholars suggesting this could both expand the First Amendment Forum doctrine while also narrowing the definition of government speech.¹⁵⁴

¹⁴⁸ Benjamin L Fu & Dohyun Kim, *What to expect next in the Harvard Admissions Suit News*, THE HARVARD CRIMSON (Oct. 13, 2020), <https://www.thecrimson.com/article/2020/10/13/harvard-sffa-next-steps/> [perma.cc/YFC8-S443] (citing Professor Vinay Harpalani claiming that the case is an attempt to challenge *Grutter v. Bollinger*).

¹⁴⁹ *Id.*

¹⁵⁰ Petition for Writ of Certiorari at 15, *New York State Rifle & Pistol Association Inc. v. Bruen*, 142 S.Ct. 2111 (2022) (No. 20-843).

¹⁵¹ See e.g., Ali Rosenblatt, *Proper Cause for Concern: New York State Rifle & Pistol Association v. Bruen*, 17 DUKE J. CONST. L. & PUB. POL'Y Sidebar 239, 260 (2022) (Discussing the possible impact of *Bruen* on state restrictions on firearms).

¹⁵² Brief for the Petitioners at 21, *Shurtleff v. City of Boston*, 42 S.Ct. 746 (2022) (No. 20-1800).

¹⁵³ *Id.* at 22–23.

¹⁵⁴ See e.g., Steven D. Schwinn, *Did the City of Boston Violate Free Speech When It Declined a Request by a Private Organization to Fly "the Christian Flag" on the City's Flagpole outside City Hall?*, 49 PREVIEW U.S. SUP. CT. CAS. 27, 30 (discussing the implications of the Court's determination of the flag as government or private speech).

For *United States v. Tsarnaev*, 20-443, the model predicts the Supreme Court will reverse and or vacate, with the case being remanded. In *Tsarnaev*, petitioner first alleged that the lower court abused its supervisory power when limiting the voir dire power of a district court in questioning jurors on bias.¹⁵⁵ Petitioner then contended that the lower court erred by finding that the District Court abused its discretion and violated the Eighth Amendment in excluding the Waltham murders during sentencing, which may have been marginally relevant to mitigating evidence.¹⁵⁶ SCOTUS_AI predicts the Court will reverse, which may reaffirm the broad discretionary power District Courts hold in evidence consideration.¹⁵⁷

All of these predictions, some of which have already come true at both the time of writing of this paper and its corresponding peer review, demonstrate the practical utility to our model. While a legal dialogue is necessary to understand the meaning of the results, SCOTUS_AI can be a useful tool in identifying probable outcomes.

XIII. Limitations and Future Research

There are several significant limitations to the study that affect interpretability and will require future improvements. First, Deep Neural Networks (DNNs) are inherently difficult to interpret, both for the reasoning and individual relationships between variables.¹⁵⁸ Thus, to gain insight into how the model may be responding, individual studies will need to assess how each variable interacts. Moreover, because DNNs are not parametric and reason by differing layers of variable interactions at different frequencies, future researchers will need to similarly analyze variable relationships using nonparametric methodologies. Thus, future studies that wish to understand the relationships within our algorithm will either need to develop new strategies, or run various

¹⁵⁵ See Petition for A Writ of Certiorari at 16-21, *United States v. Tsarnaev*, 142 S.Ct. 1924 (2022) (No. 20-443).

¹⁵⁶ *Id.* at 27.

¹⁵⁷ See Alan Raphael & Lindsay Hill, *Did Voir Dire and Discovery Restrictions Justify the Grant of a New Sentencing Hearing to the Man Convicted of the Boston Marathon Bombing?*, 49 PREVIEW U.S. SUP. CT. CAS. 38, 43 (Explaining that a rejection of the 1st Circuit’s application of Patriarca through reversal would affirm that the district court acted appropriately).

¹⁵⁸ Thomas Wischmeyer, *Artificial Intelligence and Transparency: Opening the Black Box*, 31 HARV. J. L. & TECH. 890, 890–91 (2018) (“[T]he law is built on legal doctrines that are focused on human conduct, which when applied to AI, may not function.”).

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

regressions variable-to-variable at different points of distribution.¹⁵⁹ Furthermore, because DNNs are stochastic, replication is not easily available.¹⁶⁰

Second, while the webscraper sorted the majority of cases correctly by result, approximately 6% of cases were recorded incorrectly. As a result, each case was manually checked by research assistants and then finally checked by authors. While improbable, it is possible that errors were missed. Regardless, a large sample makes these incorrect data points likely irrelevant to the overall performance of the model.¹⁶¹

Third, LIWC itself suffers from several deficiencies. First, as with almost all sentiment analyzers that record only frequency, LIWC struggles to sort language by context.¹⁶² For example, LIWC cannot distinguish sarcastic statements from genuine but similar ones. Likewise, LIWC does not directly account for certain “coded” contexts, like when advocates cite a case that holds heavy connotations (such as *Roe v. Wade*). It is possible, however, that LIWC accounts for this, given the diction surrounding a case’s citation. But, legal documents being generally straightforward in argumentation might account for this effect. These relationships, while possible, are largely speculative and will require future research. Future studies, which will likely employ LIWC2022 over our legacy use of LIWC2015, can possibly help to improve these accounts. New tools with LIWC2022, like the narrative tracker, can help improve future predictions.

Moreover, because LIWC has difficulty with contexts, it is not clear if ideology has a confounding or mediating relationship with psychological priming.

¹⁵⁹ Grégoire Montavon et. al, *Methods for Interpreting and Understanding Deep Neural Networks*, 73 DIGITAL SIGNAL PROCESSING 1 (2018) (explaining that even though there have been several practical successes to DNNs, interpreting deep networks remains difficult); See also C. Zhang & Philip C. Woodland, *Parameterised Sigmoid and ReLU Hidden Activation Functions for DNN Acoustic Modeling*, 2015 INTERSPEECH 3224 (2015).

¹⁶⁰ Samek et al., *supra* note 86, at 251; See generally YAN YAN ET AL., *A Unified Analysis of Stochastic Momentum Methods for Deep Learning*, PROCEEDINGS OF THE TWENTY-SEVENTH INTERNATIONAL JOINT CONFERENCE ON ARTIFICIAL INTELLIGENCE 2955 (2018); JASON BROWNLEE, *What does stochastic mean in machine learning?* MACHINE LEARNING MASTERY (last updated Jul. 24, 2020), <https://machinelearningmastery.com/stochastic-in-machine-learning/> [perma.cc/QMV4-R859] (“It is a mathematical term and is closely related to ‘randomness’ and ‘probabilistic’”).

¹⁶¹ J. P. VERMA & PRIYAM VERMA, DETERMINING SAMPLE SIZE AND POWER IN RESEARCH STUDIES 61–88 (2020); But see J. Wittes, *Sample size calculations for randomized controlled trials*, 24 EPIDEMIOLOGIC REV. 39–53 (2002) (arguing that the importance of sample size when the depending prediction is important).

¹⁶² Tausczik & Pennebaker, *supra* note 51, at 30; Vogel & Pechmann, *supra* note 58, at 60.

Some scholars have suggested it does.¹⁶³ But others have argued that any relationship between ideology and psychological priming is not impactful.¹⁶⁴ But if there was a significant relationship between ideology and psychological preference in legal arguments, one would suspect that the changing composition of the Court—for example, from the beginning of the Robert’s Court to the changes of composition under President Trump—would then relate to the psychological priming of the court for each case. Regardless of whether time is related to psychology, there may still be a pervasive ideological effect on certain classes of cases. Scholars have argued that certain types of cases, especially those relating to gay marriage or abortion, may have different perceptual effects on judges.¹⁶⁵ But it is not clear if this would optimize the actual performance of the model, as it may already control for this effect by reading a case class by certain psychological cues. Because DNNs are not easily readable, future scholars will need to investigate whether this is the case.

Fourth, while SCOTUS_AI can effectively predict how a single brief can predict the results of a case, it cannot predict how response briefs temporally affect outcomes—that is, while AI can read response briefs, it cannot recognize, outside of the words the brief uses, that the response brief is filed after the petition. In doing so, the algorithm assumes brief independence—namely, that briefs can be used to predict outcomes without reading other briefs. On the one hand, this allows individual practitioners to predict a case’s outcome earlier in the process. On the other hand, the briefs are not read in context. This is especially problematic if a rebuttal brief is being filed. Rebuttals are read the same as the initial petition by the machine, as it was only trained on government briefs, of which most are petitions. This does not matter if one assumes that psychological priming is independent of legal arguments—that is, that the framing of an argument matters more than the argument itself—as the context of a rebuttal’s response would be irrelevant. Future studies will need to determine whether this is the case.

Fifth, there are several ethical implications to consider when deploying SCOTUS_AI in the field. As with all artificial intelligence, SCOTUS_AI can consistently apply standards to predict the status quo.¹⁶⁶ The status quo, however,

¹⁶³ Black et al., *Emotions, Oral Arguments*, *supra* note 61, at 557 (demonstrating there is an empirical relationship between word use and ideology); *But see* Ruger et al., *supra* note 24, at 1159 (explaining that it is difficult to identify the role of ideology in law).

¹⁶⁴ *See* Black et al., *The Role of Emotional Language*, *supra* note 70, at 19 (suggesting there is some effect, with ideology not fully mediating emotional priming).

¹⁶⁵ *See generally* Daniel C. Lewis et. al, *Public Opinion and Judicial Behavior in Direct Democracy Systems: Gay Rights in the American States*, 14 STATE POLITICS & POL. Q. 367 (2014).

¹⁶⁶ Mike Zajko, *Conservative AI and Social Inequality: Conceptualizing Alternatives to Bias through Social Theory*, 36 AI & SOC’Y 1047, 1048 (2021) (“[T]he vast amorphous terrain of

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

may reproduce undesirable inequalities, biases, or prejudices.¹⁶⁷ As some scholars have noted, DNNs often develop racist or sexist undertones when exposed to open dialogue.¹⁶⁸ A ProPublica study, for example, demonstrated that an artificial intelligence deployed in Florida falsely flagged black defendants at twice the rate of white ones.¹⁶⁹ This means that those using a DNN must understand that its purpose is to consistently apply the standards as they exist in the status quo, good or bad. SCOTUS_AI specifically informs us how efficient a brief is in psychologically priming the Supreme Court to be receptive or unreceptive to certain arguments. Moreover, it is possible that actor self-awareness of the algorithm will impact future use of SCOTUS_AI and similar algorithms. Thus, at best, SCOTUS_AI can consistently identify human social psychology and connect it to case outcomes. At worst, it could reinforce a harmful status quo.

Finally, as machine creativity increasingly begins to mirror human intelligence and gain the characteristics of consciousness, it is equally important that researchers consider the implications of deploying such machines into the legal industry.¹⁷⁰ While larger, more abstract concerns of the ‘singularity’—the

societal bias includes inequalities and injustices that can indeed be accurately reproduced, and therefore reinforced, by an algorithm.”); *See generally* ANTHONY ELLIOTT, *THE ROUTLEDGE SOCIAL SCIENCE HANDBOOK OF AI* (2022).

¹⁶⁷ Maxi Scherer, *Artificial Intelligence and Legal Decision-Making: The Wide Open?* 36 J. OF INT’L ARBITRATION 559 (2019) (“[A] blind deferential attitude towards algorithmic objectivity and infallibility is misplaced. AI research over the past years has highlighted the risks of misbehaving or biased algorithms. Important studies discuss bias concerns in computer systems used for a variety of tasks, such as flight listings, credit scores, or on-line advertisements.”); JESPER RYBERG & JULIAN V. ROBERTS, *SENTENCING AND ARTIFICIAL INTELLIGENCE* 242 (2022) (“Machine learning looks for relations between characteristics that best predict the outcome. It does not look for characteristics that should affect the punishment according to legal principles.”).

¹⁶⁸ Zajko, *supra* note 154, at 1047 (“Scholars have documented the ways that automated decisions are depriving people of government benefits, discriminating on the basis of sex, skin color, age and numerous other forms of difference, choosing who is surveilled, who is imprisoned, or who is targeted for economic exploitation.”); *See, e.g.*, Will Douglas Heaven, *How to Make a Chatbot That Isn’t Racist or Sexist*, MIT TECH. REV. (Oct. 23, 2020), <https://www.technologyreview.com/2020/10/23/1011116/chatbot-gpt3-openai-facebook-google-safety-fix-racist-sexist-language-ai/> [<https://perma.cc/HF6N-EUNV>] (explaining that neural trained chatbots, such as GPT-3, that learn from the internet often take on explicitly racist or sexist opinions).

¹⁶⁹ Jonathan Shaw, *Artificial Intelligence and Ethics*, HARVARD MAGAZINE (Jan.-Feb. 2019), <https://www.harvardmagazine.com/2019/01/artificial-intelligence-limitations> [<https://perma.cc/WL4P-UAA3>].

¹⁷⁰ Filippo Raso et al., *Artificial Intelligence & Human Rights: Opportunities & Risks*, Berkman Klein Center 18 (2018) (“[T]hey require constant attention by those who are responsible for the design and operation of such systems to ensure that their outputs are consistent with evolving notions of fairness.”); Frederick Kile, *Artificial Intelligence and Society: A Furtive Transformation*, 28 AI & SOC’Y 107–15 (2012) (explaining that the intersection of AI effects range from philosophical debates on human free will to mass media, cybercrime, and war). *But see*

fear that super intelligent computers, upon gaining consciousness, will attempt to subjugate humanity—is improbable at the given state of AI. Advancements in Computational Theory of the Mind does suggest that machines may be able to, upon being given considerable capital in our legal system, subtly influence society.¹⁷¹ For the judiciary specifically, offering unfettered jurisdiction to machines may have considerable implications on human liberties; the science fiction staple, *The Minority Report*, provides one dystopian narrative, with human ‘precogs’ able to predict future crimes before they are committed and direct law enforcement to intervene.¹⁷² Replace ‘precogs’ with artificial intelligence, and the analogous threat to human free will, as well as due process assumptions, becomes obvious.¹⁷³

A number of real life algorithms, similar to SCOTUS_AI, are being actively field tested; “Sweetie,” for example, is a chatbot designed to combat human trafficking by determining those at high risk of pedophilic activity, and then interacting with such online predators to provide evidence for law enforcement activity.¹⁷⁴ BRAINS and HOLMES 2, likewise, can model the

Gunter Meissner, *Artificial Intelligence: Consciousness and Conscience*, 35 AI & SOCIETY 231 (“It will be in particular difficult for a machine to achieve advanced stages of consciousness, i.e., reflective consciousness, which constitutes properties such as: (1) metacognition, i.e., the ‘second derivative’ of consciousness such as awareness of awareness, thinking about thinking, or knowledge of knowledge and (2) volition, the free will to make choices and act on them, often used synonymous with ‘willpower’... Only 3% of the AI researchers believed that artificial consciousness can be generated by applying existing ideas. 16% of AI researchers thought that current ideas provide at least an outline of a solution, while 32% of researchers believed that artificial intelligence may be eventually achieved, but it will require new ideas”); *But see also*, Nick Bostrom, *The Ethics of Artificial Intelligence, in Artificial Intelligence Safety and Security*, at 48 (Eliezer Yudkowsky ed., 1 ed. 2018) (arguing that “with sufficiently advanced mental states, or the right kind of states, will have moral status, and some may count as persons.”).

¹⁷¹ Meissner, *supra* note 170, at 229 (“Currently humans, due to their intelligence, control every other species on earth. However, fear exists that self-learning computers or robots will become ‘super intelligent’, use their intelligence to become ‘super powerful’ and uncontrollable by humans, a scenario called ‘singularity’... While currently (2019), few robots and deep-learning computers that pose a danger exist, the threat will become real in the future.”).

¹⁷² Ernesto Edwards, *How to Stop Minority Report from Becoming a reality: Transparency and accountability of Algorithmic Regulation*, (2021) <https://ssrn.com/abstract=3997871> (“Accused not of crimes they have committed, but of crimes they will commit. It is asserted that these men, if allowed to remain free, will at some future time commit felonies.”).

¹⁷³ Laura Stănilă, *Minority Report: AI Criminal Investigation*, International Scientific Conference “Towards a Better Future: Human Rights, Organized Crime and Digital Society” 141–142 (2020); *See also* Tibi Puiu, *Scientists Urge Ban on AIS Designed to Predict Crime, Minority Report-style*, ZMESCIENCE (Jun. 30, 2020), <https://www.zmescience.com/science/ban-ai-predictive-crime-0523623/> [<https://perma.cc/3ANC-MM3G>] (“A controversial research employing automated facial recognition algorithms to predict if a person will commit a crime is due to be published in an upcoming book. But over 1,700 experts, researchers, and academics from AI research have signed an open letter opposing such research, citing ‘grave concerns’...”).

¹⁷⁴ Stănilă, *supra* note 173, at 148–49.

profiles of criminals, assisting in both reactive criminal investigation and proactive criminal prevention.¹⁷⁵ Most recently, China has comprehensively incorporated artificial intelligence into the judiciary, with system 206 included for “case filing, investigation, approval for arrest, review, prosecution, court trial, [and] conviction,” and is allegedly 97% accurate.¹⁷⁶ As the Chinese government has argued, system 206 represents a breakthrough in social governance by improving the efficiency of analyzing cases.¹⁷⁷ But, others have suggested that System 206 could threaten individual liberties by incentivizing conduct friendly to the Chinese Communist Party—for example, by accurately and aggressively prosecuting political dissent.¹⁷⁸ China is not alone in these advancements; other researchers in the United States, for instance, have developed convolutional algorithms that can use existing CCTVs to detect “social distancing breaches” and “discreetly alert relevant people to move apart.”¹⁷⁹

To summarize the ethical implications of AI, we present several, unresolved questions: first, how does AI impact issues of legal equality? Legal maxims, such as *mens rea*, become considerably more difficult to understand upon the deployment of complex machine learning algorithms that can understand and predict for human psychology. Does the nature of predicting criminal activity deprive individuals of their due process rights? Does exploiting high-risk individuals, as “Sweetie” does, to commit crimes have implications of the

¹⁷⁵ Stănilă, *supra* note 173 at 145; See also Giles Oatley & Brian Ewart, *Data Mining and Crime Analysis*, 1 WILEY INTERDISCIPLINARY REVIEWS: DATA MINING & KNOWLEDGE DISCOVERY 150 (2011) (“HOLMES2 builds upon operational practice. A code of practice that is the UK’s National Intelligence Model describes nine ‘analytical techniques,’ which include crime pattern analysis and network analysis.”).

¹⁷⁶ Jack Newman, *China Develops AI ‘Prosecutor’ that can Press Charges ‘With 97% Accuracy’*, DAILY MAIL ONLINE (Dec. 27, 2021), <https://www.dailymail.co.uk/news/article-10346933/China-develops-AI-prosecutor-press-charges-97-accuracy.html> [<https://perma.cc/2GQR-KHYF>]; ‘More than 97% accuracy’: Chinese scientists Develop AI ‘Prosecutor’, THE KOREA TIMES (Dec. 26, 2021), https://www.koreatimes.co.kr/www/world/2021/12/672_321168.html [<https://perma.cc/G26N-2282>]; Yadong Cui, Cao Yan & Liu Yan, *Artificial Intelligence and Judicial Modernization*, at vi (2020); See generally George G. Zheng, *China’s grand design of People’s Smart Courts*, 7 ASIAN J. L. & SOC. 561–82 (2020).

¹⁷⁷ See Ran Wang, *Legal Technology in Contemporary USA and China*, 39 COMP. L. & SEC. REV. 1, 15 (2020); Cui, Yan & Yan, *supra* note 177, at xvii (“The success of the 206 System is a breakthrough in the integration of technological rationality, legal rationality, and human rationality”); See also Cui, Yan & Yan, *supra* note 177, at 137 (explaining that the 206 system now handles 100% of all common crimes).

¹⁷⁸ Ji Weidong, *Judicial reform in China: The Status Quo and Future Directions, Towards the Rule of Law in China*, 20 IND. J. OF GLOB. LEGAL STUD. 138, 138–256 (2022) (“this automatic and speedy operation system of criminal sentencing is nothing but a horrible ongoing meat grinder... If software has already set the only correct answer, it is then almost meaningless to have court discourses...”); See generally STEVEN FELDSTEIN, *THE RISE OF DIGITAL REPRESSION* (2021).

¹⁷⁹ Adarsh Jagan Sathyamoorthy et al., *COVID Surveillance Robot: Monitoring Social distancing constraints in indoor scenarios*, 16 PLOS ONE (2021); Monika Zalmierute et al., *The Rule of Law and Automation of Government Decision Making*, 82 THE MODERN L. REV. 425, 425 (2019).

standard for entrapment? Second, what are the dangers of deploying AI in the judiciary? In the civil sphere, would exploiting the deep rooted, emotional state of Justices to produce desirable results have ethical implications, as SCOTUS_AI may one day be able to do? Is there a tangible threat of a ‘singularity’ moment, with AI able to subtly influence human conduct, as Facebook’s algorithm already can? And third, should the legal system more definitively favor an assumption of free-will or risk probability assessments? Does the ‘compelling governmental interest’ of protecting human life justify increasingly intrusive machines, able to subtly but impactfully influence our behavior? A better question, in general, may be if society is willing to forgo previously idealized rights of privacy and due process for the safety and security of an automated government.

While this paper does not take an affirmative stance on these ethical issues, it is important that future researchers and engineers recognize the danger artificial intelligence may pose.

XIV. Conclusion

As the results illustrate, SCOTUS_AI outcompetes a number of traditional methodologies. Thus, there is value to assessing a more detached psychological framing of a case, even for contentious debates on constitutional rights. In terms of theory, our model also defies more cynical expectations of Supreme Court decision-making being unpredictable. While our model undermines certain expectations and predictability by institutionalists, the current model cannot be wholly divorced from legal reasoning for several reasons. First, it is possible that the rules act as psychological primers detected by our model, and thus SCOTUS_AI simply, more concisely, tracks a mediating effect institutionalists already theorize. Second, even if psychological primers were independent of the rules, our model’s predictions are practically unintelligible without an institutionalist framework of interpreting what court outcomes, such as “reverse” or “affirm,” mean in context. Third, because the reasoning of DNNs are inherently unintelligible to a human researcher, further studies will need to assess how each variable works to influence decisions. Fourth, our model is fully functional for single-brief predictive modeling: any scholar or attorney can download our model, execute the program, and cast predictions for any brief submitted to the Supreme Court. Practitioners can also use the algorithm to improve the probability of success, although doing so will require trial and error until further research determines how each variable operates.

Finally, as we noted under limitations, we want to provide an explicit, ethical disclaimer as to the nature of SCOTUS_AI. As has been written frequently about other algorithms,¹⁸⁰ especially in systems that emphasize high specificity in

¹⁸⁰ See, e.g., Scherer, *supra* note 167, at 559.

Predicting Precedent: A Psycholinguistic Artificial Intelligence in the Supreme Court

legal outcomes, these systems can be used to reinforce prejudices and pre-existing biases. In fact, SCOTUS_AI likely optimizes to meet these preferences, as represented by (hopefully) unconscious patterns of psychological priming. The conjunction between artificial intelligence’s highly predictive and thus profitable nature and the inability of researchers to understand how the layers in a given DNN work, will likely pose an increasingly difficult problem for society. SCOTUS_AI, while an accurate tool to measure probability, is not a judge. While we hope that *Ruger*’s sentiment—that interdisciplinary studies can “enhance the gradually increasing dialogue between [sic] two disciplines”—remains true, we also acknowledge the danger that social engineering poses to a society where all are treated equally under the law.¹⁸¹ To quote Chief Justice Roberts: “[AI’s] day [is] here... and it’s putting a significant strain on how the judiciary goes about doing things.”¹⁸²

¹⁸¹ Ruger et al., *supra* note 24, at 1194.

¹⁸² Adam Liptak, *Sent to Prison by a Software Program’s Secret Algorithms*, THE NEW YORK TIMES (May 1, 2017), <https://www.nytimes.com/2017/05/01/us/politics/sent-to-prison-by-a-software-programs-secret-algorithms.html> [<https://perma.cc/JS3Z-5F2S>].