THE PRESENT AND NEAR FUTURE OF SELF-DRIVING CONTRACTS

Anthony J. Casey & Anthony Niblett*

1. INTRODUCTION

Over the last six years, there has been a tidal wave of research examining the potential effects of artificial intelligence[1] on the law.[2] As some early predictions from that literature begin to play out, small changes in the legal landscape are taking shape. This provides an opportune moment to take stock. In this chapter, we do that with regard to AI's effects on automated private contracts. We assess where some relevant technology stands today, where things are headed in the near future, and what this means for contract law.

As this latest AI trend in legal scholarship was taking early form in 2015, we introduced the idea of the micro-directive—a legal technology that uses AI-augmented algorithms to translate the purpose of a law into a

* Anthony J. Casey is the Donald M. Ephraim Professor of Law and Economics and the Faculty Director of the Center on Law and Finance at the University of Chicago Law School. Anthony Niblett is an Associate Professor at the University of Toronto Faculty of Law, the Canada Research Chair in Law, Economics and Innovation, and a faculty affiliate at the Vector Institute of Artificial Intelligence. Casey acknowledges financial support from the Richard M. Weil Faculty Research Fund and the Paul H. Leffmann Fund. Niblett acknowledges financial support for this project from SSHRC and the Canada Research Chair program. In the interests of full disclosure, Niblett is the co-founder of Blue J Legal, a start-up bringing machine learning to tax law and employment law.

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[1] Much of the literature has discussed the growth and importance of predictive technologies such as supervised machine learning. In this article we use the term 'artificial intelligence' or 'AI' broadly—and somewhat imprecisely—to encompass these various predictive technologies that facilitate automated decision-making based on data analytics.

[2] *See generally* Catalina Goanta, Gijs van Dijck & Gerasimos Spanakis, 'Back to the Future: Waves of Legal Scholarship on Artificial Intelligence' in Sofia Ranchordás & Yaniv Roznai (eds.) *Time, Law, and Change: An Interdisciplinary Study* (Oxford: Hart Publishing, 2020) 327 (showing the increased attention artificial intelligence has received in legal scholarship in recent years); *see also* Benjamin Alarie, 'The path of the law: Towards legal singularity' (2016) 66:4 *UTLJ* 443; Gillian K. Hadfield, *Rules for a Flat World* (Oxford: Oxford University Press, 2016); Rory Van Loo, 'Rise of the Digital Regulator' (2017) 66:6 *Duke LJ 1267;* Aziz Z. Huq, 'A Right to a Human Decision' (2020) 106 *Virginia LR* 611.

specific legal directive.[3] That directive is communicated to the relevant party at the moment it becomes useful. Importantly, the directive is context specific, and so the content of the law effectively changes to fit each situation to which it is applied.[4]

In 2016, we took this idea in a new direction, exploring the possibility of using micro-directives in private contracts.[5] In that context, private parties use micro-directives to fill gaps or update contract provisions that would otherwise be incomplete or inflexible.[6] We posited that data-driven predictive algorithms, specified up front, could give the parties context-specific directives on how to comply with a contract's purpose. Thus, rather than relying on human referees to fill gaps and reform provisions after disputes arise, these contracts would rely on micro-directives—which gather data about the current state of the world and factor in the purpose of the contract—to update the parties' obligations at the time of performance.

We referred to these automated private agreements as 'self-driving contracts.'[7] Just as passengers in a self-driving car input a destination and let the car do the rest, parties to a self-driving contract simply specify their ex ante objective (for example, maximize joint surplus) and let the contract's algorithms flesh out the details of their relationship. And just as the car collects data and updates its route to account for changing traffic patterns and road conditions, the contract's algorithms utilize data and update the parties' rights and obligations to account for the changing context of their relationship.[8]

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[3] Anthony J. Casey & Anthony Niblett, 'The Death of Rules and Standards' (2015) working paper available at: <https://chicagounbound.uchicago.edu/cgi/-viewcontent.cgi?article=2444&context=law_and_economics>. For the final published version see Anthony J. Casey & Anthony Niblett, 'The Death of Rules and Standards' (2017) 92 *Indiana L.J.* 1401. All citations to this paper below are to the published version.

[4] *Ibid* at 1410.

[5] Anthony J. Casey & Anthony Niblett, 'Self-Driving Laws' (2016) 66 *University of Toronto Law Journal,* 429 at 440-441. We expanded on this analysis in Anthony Casey & Anthony Niblett, 'Self-Driving Contracts' (2017) 43 *J Corp L* 1.

[6] Casey & Niblett, 'Self-Driving Contracts,' supra note 5, at 13-15.

[7] Others have referred to these and similar contracts as 'algorithmic contracts.' *See* Lauren Henry Scholz, 'Algorithmic Contracts' (2018) 20 *Stan Tech LR* 128. In an earlier article, Harry Surden referred to a related concept of a 'Data-Oriented Contract.' *See* Harry Surden, 'Computable Contracts' (2012) 46 *UC Davis LR* 629.

[8] Importantly, self-driving contracts are distinct from 'smart contracts.' The former involves contracts that use micro directives to automate the creation of substantive terms, while the later involves certain technologies, like blockchain, to provide a self-execution mechanism. *See generally* Nick Szabo, 'The Idea of Smart Contracts' (1997) available online at: <http://szabo.best.vwh.net/smart_contracts_idea.html>. Much has been written on smart contracts in recent years. *See, e.g,.* Dirk A Zetzsche, Ross P Buckley & Douglas

The ideas of the micro-directive and the self-driving contract have been the subject of much scrutiny and critique.[9] Some scholars were skeptical that micro-directives and self-driving contracts were even possible.[10] And, at a high level of abstraction, the idea of a fully self-driving contract does bring to mind science fiction examples of conscious automatons controlling human behavior.

Yet when one considers things at a more specific level, it becomes clear that micro-directives have actually existed in early form for decades. The standard traffic light can be viewed as a micro-directive.[11] Similarly, self-driving contracts cannot accurately be classified as science fiction when, for example, insurance companies have been using them for years.[12]

W Arner, 'The Distributed Liability of Distributed Ledgers: Legal Risks of Blockchain' [2018] *UIll LR* 1361.

While we view smart contracts as distinct from self-driving contracts, some view the self-driving contracts as an advanced type of smart contract. *See, e.g.,* Michele M van Eck, 'The Disruptive Force of Smart Contracts' in Wesley Doorsamy, Babu Sena Paul & Tshilidzi Marwala, eds., *The Disruptive Fourth Industrial Revolution* (Cham: Springer, 2020) 21; Joshua S Gans, 'The Fine Print in Smart Contracts' (2019) *NBER Working Paper* No. w25443.

[9] For discussions and criticisms of our earlier work, *see* Jamie Susskind, *Future Politics* (Oxford: Oxford University Press, 2018); Frank Pasquale, 'A Rule of Persons, Not Machines: The Limits of Legal Automation' (2019) 87 *Geo Wash LR* 1*;* Mark A. Lemley & Bryan Casey, 'Remedies for Robots' (2019) 86:5 *UChi LR* 1311; Dan L. Burk, 'Algorithmic Fair Use' (2019) 86 *UChi LR* 283; Christoph Busch, 'Implementing Personalized Law: Personalized Disclosures in Consumer Law and Data Privacy Law' (2019) 86 *UChi LR* 309; Carla L. Reyes, Mireille Hildebrandt, 'Law as computation in the era of artificial legal intelligence: Speaking law to the power of statistics' (2018) 68 *UTLJ* 12; David Freeman Engstrom, Daniel E Ho, Catherine M Sharkey. & Mariano-Florentino Cuellar, 'Government by Algorithm: Artificial Intelligence in Federal Administrative Agencies' (2020) *NYU School of Law, Public Law Research Paper* No. 20-54; Katherine J. Strandburg, 'Rulemaking and inscrutable automated decision tools' (2019) 119:7 *Colum LR* 1851.

[10] Many criticisms take issue with the idea of a fully self-updating contract. These critiques question the extent to which AI is able to tailor contractual positions for all or nearly all possible contingencies. *See, e.g.* Spencer Williams, 'Predictive Contracting' [2019] *Colum Bus LR* 621 at 674; Eric Tjong Tjin Tai, 'Force majeure and excuses in smart contracts' (2018) 26:6 *Eur Rev Priv L* 787; Benito Arruñada, 'Prospects of blockchain in contract and property' (2020) 8:3 *Eur Prop LJ* 231 at 234; Ralph Schuhmann, 'Quo Vadis Contract Management? Conceptual Challenges Arising from Contract Automation' (2020) 16:4 *Eur Rev Contract L* 489 at 500.

[11] *See* Casey & Niblett, 'Death of Rules and Standards,' supra note 3, at 1416-1417.

[12] *See, e.g.* Yiyang Bian *et al.,* 'Good drivers pay less: A study of usage-based vehicle insurance models' (2018) 107 *Transportation Research Part A: Policy and Practice* 20; Angelo Borselli, 'Insurance by Algorithm' [2018] *Eur Ins LR* 40; Angelo Borselli, 'Smart Contracts in Insurance: A Law and Futurology Perspective' in Pierpaolo Marano, (ed), *AIDA Europe Research Series on Insurance Law and Regulation* (Cham: Springer, 2020)

But what of our claims that advanced self-driving contracts will proliferate? The most compelling evidence exists in the advances that have already taken or are about to take hold. And so, while our previous work on this topic has taken the form of longer-term thought experiments, this chapter explores existing data-driven AI technologies that can facilitate the automation of specific contract provisions today. The purpose of this exploration is to uncover the present and near future of self-driving contracts.

The remainder of this chapter proceeds as follows. In section 2, we explore specific examples of existing technologies that are being or can be used to construct real-life self-driving contract provisions. We illustrate what the technology can do and describe how it will be deployed in the near future. In section 3, we discuss broader implications and lessons emerging from these examples.

2. EXISTING SELF-DRIVING CONTRACT TECHNOLOGY

As we discuss in this section, several recent developments in AI contracting represent meaningful early steps in the evolution of self-driving contracts. These advances provide proofs of concept, as well as a set of prototypes for examining the opportunities and challenges that self-driving contracts present for private law.

While the theoretical ideal of a complete self-driving contract would govern every aspect of a private relationship, the technology developments we discuss here support and advance the automation of specific and often narrow contract provisions.[13] Such provisions are, after all, the building blocks of the complete self-driving contract. Indeed, the automation of a single provision governing even a narrow aspect of a private transaction does itself represent the emergence of a self-driving contract. It is therefore useful to start our analysis with technologies that facilitate these discrete provisions.

We provide four current examples of how existing AI-augmentation and prediction technology can automate the operation of different types of contract provisions.

2.1 Dynamic pricing: Automating price of performance

101 at 108 (on dental insurance companies adjusting rates based on a smart toothbrush that tracks an individual's oral hygiene).

[13] In discussing the development of technology in the law, David Freeman Engstrom and Jonah B. Gelbach point out that the adoption of legal technology will be incremental and arrive sooner in areas with abundant data and regulated conduct that takes repetitive, stereotypical forms. *See* David Freeman Engstrom & Jonah B. Gelbach, 'Legal Tech, Civil Procedure, and the Future of Adversarialism' (2020) 169 *UPa LR* 1001.

Technology

Perhaps the term most obviously susceptible to automation in a contract is the price term. Of course, there is nothing particularly new about AI-augmented pricing algorithms. Dynamic pricing algorithms are used in many contexts to better reflect rapid changes in demand and supply. Uber's pricing mechanism presents a familiar example of dynamic pricing.[14] The price of an Uber journey adjusts automatically and frequently depending on how many users demand rides and how many drivers are available. Such algorithmic pricing technologies are pervasive in spot markets. Other prominent examples include Amazon's pricing strategies[15] and pricing in the airline industry.[16]

Application to self-driving contracts

Just as pricing algorithms are used to specify spot market prices, AI-augmented algorithms can dynamically and automatically adjust the prices in longer-term contracting relationships. Instead of 'agreeing to agree' to a future price based on changed circumstances—as they often do—the parties can agree to abide by the algorithmically-derived price, even though it is unknown at the time of contracting.

Such dynamic pricing clauses are already in use. As we noted in 2017:

> 'The most familiar example can be found in the auto-insurance industry, where parties agree to price terms that adjust automatically based on computer-driven analytics. Similar pricing terms can be found in dental insurance, in short-term rental agreements, and in transportation services.' [17]

With these clauses, parties have an ongoing relationship and the price of the contract changes with respect to the changing environment and actions of the parties. If you drive safely, you will pay lower premiums for your auto-insurance. If you brush your teeth more, you will pay lower premiums for your dental insurance. The algorithm is learning more about the riskiness of the customer. The prices adjust accordingly.

How it changes the contract

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[14] *See* Uber, 'How Uber's dynamic pricing model works' available at: <https://www.uber.com/en-GB/blog/uber-dynamic-pricing/> .

[15] See, *e.g.,* Robert M Weiss & Ajay K Mehrotra, 'Online Dynamic Pricing: Efficiency, Equity and the Future of E-Commerce', (2001) 6 *Va JL&Tech* 11.

[16] See, e.g., R Preston McAfee & Vera te Velde, 'Dynamic Pricing in the Airline Industry', in Terrence Hendershott (eds.) *Handbook of Economics and Information Systems* (Vol 1) (New York: Elsevier Science, 2007).

[17] Casey & Niblett, 'Self-Driving Contracts,' supra note 5, at 3.

Any price term in a long-term relationship implicitly allocates risks among the parties. For example, if parties to a long-term production contract agree to a fixed price, the producer bears the risk that production costs might increase. In a labor or supply shortage, the producer may realize a smaller profit (or even a loss) on the contract. In some cases, the change in production costs may be such that the producer chooses to cease performance and pay damages on the contract.[18]

Price adjustments can therefore be important in drafting a long-term contract. Conventional contract provisions give the parties some risk allocation options. Changing a fixed-price term to a cost-plus formula, for example, shifts the production-cost risk from the supplier to the buyer. More complex formulas set prices based on data compiled and made available by third parties.[19] For example, many financial contracts set interest rates and other prices by reference to indices reflecting market conditions.[20] Likewise, supply contracts often use industry pricing reports to create formulas.[21]

Alternatively, if the parties think that pricing formulas will be too rigid or subject to abuse, they might leave the price decision to be decided at a later date. They will thus agree to renegotiate the price as the market changes (essentially agreeing to agree), or perhaps they will let an arbitrator set the price when the market changes.[22]

Each method has pros and cons. Fixed-prices don't adjust to changing conditions. But they are less susceptible to ex post abuse and manipulation. Formulas provide some flexibility, but they can be manipulated. Renegotiation allows total flexibility, but renegotiation is costly and the parties can abuse the flexibility.[23] Arbitration provides

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[18] The buyer, on the other hand, might bear the risk that the good being produced will become less valuable or obsolete while she still has to pay full price for it.

[19] See Gabriel V. Rauterberg and Andrew Verstein, 'Index Theory: The Law, Promise and Failure of Financial Indices' (2013) 30 *Yale J Reg* 101.

[20] Until recently LIBOR, discussed later when we talk about data manipulation. *See* infra, text accompanying notes 56-7.

[21] *See, e.g.* Frederic R. Curtiss, Phillip Lettrich, & Kathleen A Fairman, 'What Is the Price Benchmark to Replace Average Wholesale Price (AWP)?' (2010) 16:7 *J of Managed Care & Specialty Pharmacy* 492.

[22] Andrew Verstein refers to these arrangements as 'ex tempore contracting,' where parties will intentionally leave gaps in the terms of their contract and delegate determination to third parties who update the contract on an ongoing basis. Examples of such contracts include dispute boards in construction contracts that inspect projects and update contractual responsibilities on an ongoing basis. *See* Andrew Verstein, 'Ex Tempore Contracting' (2014) 55 *Wm&M LR* 1869.

[23] Patrick W. Schmitz, 'The Hold-Up Problem and Incomplete Contracts: A Survey of Recent Topics in Contract Theory' (2001) 53 *Bulletin of Econ Res* 1.

flexibility, but it can also be unpredictable and subject to the human arbitrator's idiosyncratic decisions and biases.

AI-augmented pricing technology provides new options. The cost-plus pricing term is an algorithm, but a very simple one. Index pricing is more complex and introduces third-party data. But with AI-augmented pricing technologies, the algorithms are more sophisticated, processing complex data and updating more frequently.

These existing AI-pricing technologies can mitigate problems associated with incomplete contracts. Suppose a long-term contract includes an AI-augmented algorithm that determines the price. The pricing algorithm is developed with a specific objective in mind (maximize the joint surplus of the parties). Such a predictive algorithm would likely factor in the historical market prices of similar deals. It would also consider the parties' willingness to continue the relationship as the price changes.

In this setting, the parties agree to insert this algorithm into the agreement *at the time of contracting*. The actual price schedule is not known at that time, but the parties agree that this AI algorithm will fill that gap in the future.

The pricing algorithm is doing the work that is currently done by the human arbitrators, without the accompanying costs and uncertainty. The ex ante commitment to the algorithm replaces the ex post arbitration mechanism for resolving disputes. It reduces the likelihood of disputes about whether changed circumstances require or justify a new price.

In this way, self-driving contracts have the potential to improve matters on all fronts. A well-designed algorithm with quality data can provide flexible pricing that accounts for all sorts of changed circumstances and allocates risk according to the parties' joint preferences. It may even help the parties identify relevant price factors that they previously ignored.

Moreover, because the parties commit to the algorithm ahead of time, a self-driving contract limits opportunistic abuse and eliminates renegotiation costs. The parties are in essence committing to an automated arbitration that provides flexibility but prevents the parties from opportunistically trying to rewrite the contract.

Finally, well-designed algorithms can in some (but not all)[24] cases reduce the biases and idiosyncratic variance associated with human arbitration.[25]

<u>Potential use example</u>

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[24] We discuss the potential for algorithm bias and variance below when we discuss the lessons and challenges for the near future of self-driving contracts.

[25] Other scholars have explored the use of algorithms to reduce bias in other areas of the law. *See, e.g.* Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan, & Cass R Sunstein, 'Discrimination in the Age of Algorithms' (2018) 10 *J Leg Analysis* 113; Alex Chohlas-Wood *et al,* 'Blind Justice: Algorithmically Masking Race in Charging Decisions' [2020] *Technical Report*.

Consider the following possible application of pricing technology.[26] A building owner and a bank negotiate a long-term rental agreement for commercial real estate. The bank wishes to locate its corporate headquarters in the building. Together, the two parties agree that they wish to maximize their joint surplus. With this objective in mind, the parties initially agree that the lease shall last five years. The parties also agree on a monthly rental price for the five years of the lease.

The parties also include a renewal term. The renewal term is a signal that the parties wish to enter into a longer-term agreement, but are unsure about how the market for commercial leasing will look in five years. Each party acknowledges that the other party is specifically investing in the relationship.

But there is enormous uncertainty. While the parties could undertake the expense of trying to work out the most likely best price for each month of the lease for ten or fifteen years, including such a price would be costly and create enormous risk for both parties. And so the parties include an agreement to negotiate a new rental price at the time of renewal.

That agreement could require them to 'renegotiate the price in good faith.' But what if they can't reach an agreement? They might also include arbitration as a mechanism for resolving such disputes should they arise. This mechanism reduces some hold-up behavior and renegotiation costs. But, parties may be uncomfortable with uncertainty about the identity and bias of the arbitrator.

The missing content of the renewal price term thus introduces costly uncertainty, leaving the parties vulnerable to opportunistic hold up by the other side during renegotiation or arbitration. These problems reduce the parties' incentives to invest in the relationship in the first place.

But with dynamic pricing technology, the parties can do away with the fixed price portion of the lease and simply rely upon the pricing algorithm to provide month-by-month updated pricing. This is true not only for the renewal period, but also for the initial five years. Indeed, the parties might implement the updates the moment the contract begins and they might set the updates to run on a weekly or daily schedule to get an even more well-calibrated pricing schedule. If the algorithm is calibrated properly, it would reduce the need for renegotiation in the event of booms or slumps, or changes in the parties' circumstances.

2.2 Litigation analytics: Automating terms of non-performance

<u>Technology</u>

[26] The underlying facts here are loosely based on *Empress Towers Ltd. v. Bank of Nova Scotia* (1990), 73 DLR (4th) 400. But these arrangements are common and often litigated.

AI-augmented technology that is currently being used for litigation prediction can be refitted to the purpose of automating terms regarding non-performance.

In the last decade, there has been a dramatic acceleration in the development of algorithms that predict how courts and arbitrators will decide cases. Data from previous judicial decisions form the backbone of a dataset from which machine learning algorithms provide a prediction of how a judge or arbitrator would resolve questions if the parties seek ex post dispute resolution. These predictions include the likelihood that a judge will rule in one party's favor and probabilities associated with different damage awards.

These algorithms factor in the relevant features of the case; they compare these factors to all similarly litigated cases in the dataset.[27] Such predictive algorithms are already in use by lawyers and accountants to determine the merits of their positions in patent law, employment law, and tax law as well as by litigation finance firms.

<u>Application to self-driving contracts</u>

One might think that these algorithms are exclusively relevant in litigation. The thinking here is that once the parties are involved in a dispute, they can use the algorithm to better determine the strength of their position.[28] While this no doubt represents one use case of the algorithms, the parties can just as easily use them to fill gaps in their contracts.

Because the definition and price of non-performance are common subjects of litigation, parties can incorporate into their self-driving contract existing technologies originally designed for predicting litigation outcomes and damages. The contract—rather than an arbitrator or judge—could turn those predictions into micro-directives available at the relevant moment that update the definition and price of non-performance. These micro-directives could dictate what price parties will pay if they fail to perform a certain obligation or they might define exactly what constitutes non-performance in specific contexts.

<u>How it changes the contract</u>

[27] *See generally* Benjamin Alarie, Anthony Niblett, & Albert H Yoon, 'Using Machine Learning to Predict Outcomes in Tax Law' (2016) 58 *Can Bus LJ* 231; Benjamin Shmueli & Moshe Phux, 'Small Data, Not (Only) Big Data: Personalized Law and Using Information from Previous Proceedings' (2019) 35:3 *Ohio State J Disp Resol'n* 331.

[28] We have elsewhere discussed how the use of tools that predict litigation outcomes based on data from prior cases will affect litigation outcomes and settlement. *See* Anthony J Casey & Anthony Niblett, 'Will Robot Judges Change Litigation and Settlement Outcomes? A First Look at the Algorithmic Replication of Prior Cases' (2020) *MIT Comp L Rep 2.0*.

Conventional contracts do sometimes set a price for non-performance. For example, a contract may include a liquidated damages provision, specifying damages that are payable in the event that one side fails to perform its obligations. But these prices are difficult to set and do not update to take the parties' actual situation into account. As a result, most contracts are silent on the matter, leaving it to courts to set the price in ex post litigation.

As parties incorporate this technology, setting a self-driving price for non-performance, they will have clarity about how they should or should not perform. At the time of deciding whether to perform, they will have full information about the cost of not performing.

Similarly, where the contract incorporates prediction algorithms to define non-performance, the parties will know at the time they choose to perform whether a certain action is allowed.

Combining the two points, they will know both what path of action constitutes non-performance and the price they will pay for going down that path.[29] In some sense, this eliminates the possibility of 'breach' since 'damages' simply become the prices attached to one option. While labeling something as an option or a breach is semantic, the important feature here is that the party makes the decision with full information and there is little reason to litigate because the contract terms themselves match the predicted outcome of litigation.[30]

Potential use example

An illustrative example of a potential use for this technology comes from Canadian employment law. When an employment contract is silent on the question of notice, the common law implies a default term of reasonable notice. If a worker is dismissed without cause, they are entitled to a reasonable notice period, or as is more common to payment in lieu of that notice.[31] For the employer, this is the price of terminating the contract.

Reasonable notice is a vague term. What is reasonable depends on the circumstances. The frequently cited statement of law stipulates that '[t]here can be no catalogue laid out for determining what is reasonable.'[32] The calculation is complex, factoring in not only the years of service, but also the age of the terminated worker, the characteristics of the job, and the availability of similar employment.

Employers and dismissed employees frequently disagree about what constitutes *reasonable* notice. While larger employers no doubt have

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[29] *See, e.g.* Borselli, 'Smart Contracts in Insurance,' supra note 12, at 115.

[30] Casey & Niblett, 'Self-Driving Contracts,' supra note 5, at 22-23.

[31] Bardal v. Globe & Mail Ltd. (1960), 24 DLR (2d) 140 (*Bardal*).

[32] *Bardal*, at 145.

their own formulas for assessing what the notice period should be for dismissed employees, these formulas typically understate what an employee is entitled to under the common law. Thus, after failing to negotiate, parties seek the assistance of a referee to determine the employer's price of non-performance. Indeed, this specific legal issue is one of the most litigated legal matters in Canada, with thousands of published cases on this narrow question in the past half century.[33]

Parties may want to specify up front what is reasonable for all points in time over the employment relationship. But that can be difficult to do considering how much can change during the term of the agreement. But now parties can instead insert a provision agreeing to use the machine learning algorithm to calculate a specific employee's reasonable notice period at the specific moment when that employee is dismissed.

The employment contract could use predictive technology to replicate what a judge or arbitrator would do in any given situation. The provision would be a highly contextual and tailored provision that pertains only to the employee at that point in time. As time and circumstances change, so would the self-driving contractual provision. But it would not be subject to some of the problems of ex post adjudication that contracting parties are commonly concerned about.[34]

Note that data predicting Canadian litigation can even be useful in self-driving contracts involving parties who are not subject to Canadian law. Imagine parties in another jurisdiction that has no rule. The parties want to contract for reasonable notice, but they have trouble defining it and there is no precedent in their jurisdiction. They might choose to use the Canadian system as their model and create a self-driving provision that uses the Canadian data to produce micro-directives.

The applications just described would entrench the content of the Canadian judicial precedent on reasonable notice into any contract that uses it. But some parties may want a different measure of reasonable notice. For them, there are alternative sources of contract substance available. The parties may use other technologies to seek an algorithm that better describes what *they* think is 'reasonable.' For example, the algorithm could be built around data that measure how long it takes dismissed employees to find a new job. Using data on employment statistics, such an algorithm may be able to predict how long it will take a particular worker in a particular industry in a particular economy to find a similar job. This

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[33] *See* Anthony Niblett, 'Algorithms As Legal Decisions: Gender Gaps and Canadian Employment Law in the 21st Century,' (2020) 71 *UNBLR*112.

[34] These problems include judicial bias and uncertainty. *See* Thomas J. Miles & Cass R. Sunstein, 'The New Legal Realism' (2008) 75 *UChi LR* 831; Jeffrey J. Rachlinski & Sheri Lynn Johnson, 'Does Unconscious Racial Bias Affect Trial Judges?' (2009) 84 *NDLR* 1195; Anthony Niblett, 'Tracking Inconsistent Judicial Behavior', (2013) 34 *Int'l RL&Econ* 9; Allison P. Harris & Maya Sen, 'Bias and Judging' (2019) 22 *Ann'l Rev of Pol Sci* 241.

algorithm would implement a reasonable-notice rule, but it would be one that achieves a different objective to one that mimics precedent.

2.3 Legal review technology: Automating legal compliance

Technology

Today's AI-augmented algorithms can help determine whether a contractual clause is enforceable or not. Compliance logic is relatively straightforward where the law is based on bright-line rules. For example, in a promissory note, if the interest rate coded by the 'contract drafter' exceeds the legislative maximum, then the software will 'raise an error' to the coder.[35]

But even more advanced technology that can detect the meaning of particular clause is in development. Even with more general terms, studies have shown that machine learning technology can automatically identify contract clauses that are potentially not enforceable.[36] And recent scholarship has sought to use computational language models to interpret contractual clauses and provide advice. Noam Kolt, for example, has empirically tested Open AI's GPT-3 model to answer questions about whether consumers are permitted to take certain actions under standard forms.[37] Kolt finds that the technology is able to predict the 'correct' answer in 77% of his sample questions. Along a similar line, Yonathan Arbel and Samuel Becher have explored the potential of 'smart readers' that can 'read, analyze, and assess contracts, disclosures, and privacy policies.'[38]

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[35] *See* Joe Dewey, 'What if we developed legal contracts like we developed software applications?' *Medium* (Apr. 3, 2016) available at: https://medium.com/@jndewey/what-if-we-developed-legal-contracts-like-we-developed-software-applications-6f8305256c5c#.6z774clv2. *See also* Irene Ng, 'The Art of Contract Drafting in the Age of Artificial Intelligence: A Comparative Study Based on US, UK and Austrian Law' (2017) *TTLF Working Papers No. 26, Stanford Transatlantic Technology Law Forum,* available at: < https://law.stanford.edu/wp-content/uploads/2017/02/Irene-Ng-TTLF-Working-PAper-26-Art-of-Contract-Drafting.pdf>

[36] Machine learning has been used to tag clauses of contracts that are 'potentially' unfair under European consumer law. *See, e.g.,* Marco Lippi *et al*, 'CLAUDETTE: An Automated Detector of Potentially Unfair Clauses in Online Terms of Service' (2019) 27 *AI&L* 117. More generally, *see*, Hans-W. Micklitz, Przemyslaw Palka, & Yannis Panagis, 'The Empire Strikes Back: Digital Control of Unfair Terms on Online Services' (2017) 40 *J Cons Pol'y* 367.

[37] Noam Kolt, 'Predicting Consumer Contracts' (2022) 37 *Berkeley Journal of Law & Technology* (forthcoming).

[38] Yonathan A. Arbel & Samuel Becher, 'Contracts in the Age of Smart Readers' (2021) 96 *Geo Wash LR* (forthcoming).

The ability to detect and translate meaning implies a broader ability to identify and change problematic terms. This ability will facilitate the emergences of important self-driving provisions.

The application to self-driving contracts

Technology that flags illegal, unenforceable, or otherwise problematic provisions can also be adapted to automatically remove or rewrite provisions that become problematic as the law changes after the contract is agreed to.

Thus, as clauses that were enforceable when the contract was formed become unenforceable before the time of performance, the contract will update to account for the change. This change might come in the form of legislation or a court decision rendering particular provisions unenforceable. Once the technology can identify provisions that have become unenforceable, it is a small step to automatically update and adjust the contract to account for the changes in the legal environment.

How it changes the contract

To return to our self-driving car analogy: if the police temporarily block a road, the self-driving car needs to update its information and find a different route to reach the desired destination. Similarly, should a contractual clause be 'blocked' by lawmakers, an AI automated referee can find a new way to achieve the parties' objective within the new legal constraints.[39]

Conventional contracts require renegotiation, invalidation, or judicial gap filling when certain provisions become unenforceable. Questions arise about whether the invalidated term can be separated from the other contractual obligations and if so, how the change might alter the price or other obligations in the contract.

By agreeing in advance to allow the self-driving contract to reform the provision, the parties avoid the costs of renegotiation or litigation. Because the new term may affect other terms in the contract and alter the parties' allocation of risk and division of surplus, they may want to combine this technology with the pricing technology above to adjust the price to account for the changes in the law and in the content of the reformed provision. In some instances, they may also include provisions that invalidate the entire contract if the price effect is too great.

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[39] In discussing the development of personalized default rules in the law, Francesco Paolo Patti envisions these rules as a benchmark that can be used to assess whether a term is unfair. Patti notes that if the term is declared unfair, a self-driving contract can act as a personalized gap-filler to supplement the now incomplete contract through a personalized default rule. *See* Francesco Paolo Patti, 'Personalization of the Law and Unfair Terms in Consumer Contracts' (2019) *Bocconi Legal Studies Research Paper* No. 3466214 at 15.

Potential use example

This technology could be used in the context of a non-compete clause in an employment contract. Such a clause may prohibit an employee from working for a firm that competes with the employer for a period of time after the current employment relationship has ended.

These clauses are treated differently in different jurisdictions. For example, such clauses are generally not enforceable in California.[40] There, the legislature has expressly prohibited the inclusion of such provisions. But in other jurisdictions, the law is vague. In Canada, for example, courts will only enforce such a clause if the employer has legitimate interests to protect and the restrictions imposed are reasonable and unambiguous.[41] Whether it is reasonable will turn on factors such as the activity that is being restricted, the geographic scope of the restriction, and the duration of the restriction.

It would be somewhat trivial to develop software that produces a red flag for any employment contract in California that includes such a clause, or one that automatically drops any such non-compete provisions from the contract.

But employers in Canada who wish to adopt a non-compete clause need to write specific and clear provisions that are tailored to the employee's role in the organization and the employer's legitimate interests. They need to be reasonable in all the circumstances.

The lawyers might spend time crafting a provision that they know courts will enforce. But what if the law changes? If Canada suddenly prohibited all non-compete clauses in employment contracts, the algorithm could simply drop the provision from the contract, and the employee could be notified that they are entitled to move positions without fear of a restrictive injunction or other remedies.[42]

But the change might be more nuanced. A court may hold that a similar – but not identical – restrictive provision is not enforceable. This move by the courts may give some partial indication about whether judges will enforce similar provisions. The self-driving contract might automatically amend the content of the contract to account for the new information. Depending on the parties' comfort with uncertainty, it might drop the provision or amend it and other related clauses to account for changes in probabilities about what a court will enforce.

Combined with litigation prediction, these review technologies can update a self-driving contract to account for even small changes reflecting incremental steps in the evolution of judicial precedent. If, in a recent case,

[40] California Business and Professions Code § 16600 (2020).

[41] *Shafron v. KRG Insurance Brokers (Western) Inc*., 2009 SCC 6.

[42] Given that this change affects the division of surplus between the parties, a more complex self-driving contract may also adjust prices accordingly.

a court held that a 12-month provision was unreasonably long, the predictive algorithm may suggest reducing a 10-month provision to 8 months, depending on the algorithm's new predictions with regard to the probability estimates and the parties' tolerance for uncertainty, which would have been incorporated in the algorithm at the time the contract was agreed to.

2.4 Negotiation technology: Automating substantive obligations

Technology

Perhaps the most advanced potential comes from existing technology that automates contract negotiation.[43] AI technologies have recently been deployed to automate contract negotiation. Data describing the terms of a contract and associated outcomes could greatly inform which specific terms are included in the contract. Automated technologies can be used to mark up contracts and suggest new terms.[44] They promise to find solutions and compromise solutions that the lawyers did not see.[45]

Sean Williams gives the example of using data to help determine which clause to include in a procurement contract:

> '[A] predictive contracting system with data on the terms and outcomes of thousands of prior procurement contracts could inform a contract drafter that version A of a delivery term is ten percent more likely to result in late performance by a particular type of counterparty than version B.'[46]

Application to self-driving contracts

The step from automated negotiation to self-driving contract provisions is small. Automated negotiation technology is valuable because it can identify terms that are acceptable to both parties. But instead of using the technology to write the contract at the time of agreement, the parties could instead agree to use the technology at the time of performance with updated data. At that point, the automated negotiation technology produces a micro-directive telling the parties how to fulfill their agreement. The technology is the same; the only difference is the timing and the data.

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[43] *See* Schuhmann, 'Quo Vadis Contract Management?' supra note 10, at 501-502.

[44] *See* Roy Strom, 'Automated Contract Negotiation Race Heats Up with Seal Entry' *Bloomberg Law* (Oct 2, 2019) https://www.news.bloomberglaw.com/us-law-week/automated-contract-negotiation-race-heats-up-with-seal-entry.

[45] *See* Jonathan Gratch, 'The Promise and Peril of Automated Negotiators' (2021) 37 *Negotiation Journal* 13.

[46] Williams, supra note 10, at 629.

How it changes the contract

Whereas parties have always been able to agree to renegotiate certain terms in the future, they can now agree to let the technology do the future negotiating for them. This provides the flexibility of renegotiation but the commitment of ex ante formulas and fixed terms.

This is the same idea we explored with regard to pricing above, but the automated negotiation technology goes further. It can, for example, create tailored instructions that indicate what *actions* constitute performance.

This can be especially useful for complex contract terms where the substantive obligations required for optimal performance turn on facts that are not known at the time of agreement and it is difficult to define the proper course of action up front. In those cases, conventional contracts often include provisions framed as vague standards using terms like 'reasonable' or 'material.' Automated negotiation technology can replace these vague standards with precise micro-directives delivered at the time of performance.

Potential use example

Take, for example, a marketing agreement where one party agrees to market and sell software created by another. It is difficult to spell out in the contract exactly what the salesperson should do in any given sales situation. Instead, the obligations of the marketer may be defined by vague guidelines such as 'best efforts' or 'reasonable commercial efforts.' But the software company may have a very different view of what *reasonable* commercial efforts means compared to the company selling the product. The software company may be disappointed by low sales and attribute this to poor effort on the part of the sales team. This vagueness creates a gap in the contract.

Automated negotiation technology could fill this gap, and when used ex post to define the parameters of the parties' obligations, it could do so in the form of micro-directives embedded in a self-driving contract.

3. IMPLICATIONS, LESSONS, AND CHALLENGES

The examples in the previous section reveal a number of lessons and challenges for self-driving contracts. We turn to those now. We explore *who* provides the algorithms and whether regulations may be necessary to ensure that automated private ordering achieves its promise. We look at what data are required for these AI-augmented algorithms to work, considering the data required for the underlying architecture of the self-driving provision and the data required to assess the context of a parties' positions. The use of such data raises issues of privacy and security and how the data will be collected, processed, used, and maintained. Further, we explore the degree to which the algorithms in the contract can actually align with the parties' objectives.

3.1 Who 'drafts' the algorithms?

One challenge to the emergence of self-driving contracts is trust.[47] Sophisticated parties may not trust each other to design algorithms that will be true to their joint purpose. If one side creates that algorithm, the other side may suspect that they will corrupt the program to favor the creator in application.

Similarly, if one party is more sophisticated than the other, there may be public policy concerns that the sophisticated party may take advantage of the unsophisticated.[48] This concern is similar to those voiced with regard to lengthy form contracts that large businesses use when contracting with consumers.[49]

One solution is government regulation of the algorithms that requires them to include certain features. Such regulation may be difficult to enforce, and in some instances, it may stifle innovation. A more attractive solution is to look to third parties to provide the algorithm, and—when necessary—the government could create regulations with regard to the independence of the provider rather than the substance of the algorithm.

We suspect that third-party developers will generate most of the content of self-driving contracts.[50] The providers of AI-augmented algorithms for self-driving contracts are likely to evolve from various existing markets. New start up software developers, harnessing the power of big data and machine learning techniques, will arise. Insurance companies, with access to enormous swathes of data on risk, may elect to

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[47] For greater discussion on this point, *see* T. T. Arvind, *A.I. and Contract Law,* in this Handbook.

[48] Gerhard Wagner and Horst Eidenmueller raise similar concerns, arguing that the risks of an extremely unequal distribution of the gains of digital dispute resolution will be to the detriment of less vigilant parties. This could impact upon the rule of law. They argue in favour of regulatory tools to control the power of large, sophisticated commercial actors. See, Gerhard Wagner & Horst Eidenmueller, *Digital Dispute Resolution*, available on ssrn at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3871612.

[49] *See, e.g.,* Margaret Jane Radin, *Boilerplate: The Fine Print, Vanishing Rights, and the Rule of Law* (Princeton: Princeton University Press, 2013).

[50] *See* Andrew Verstein, 'Privatizing Personalized Law' (2019) 86 UChi LR 551; *see also* Greg Buchak, 'Micro-Regulation in the Platform Economy' (2018) *UChi LR Online*: <https://www.law.uchicago.edu/files/2019-01/buchak1_0.pdf>; Mateusz Grochowsk, 'Default Rules Beyond a State: Special-Purpose Lawmakers in the Platform Economy' in Stefan Grundmann & Mateusz Grochowski, eds., *European Contract Law and the Creation of Norms* (Antwerp: Intersentia, 2021). We also discuss the role of these platform providers in our previous work. *See* Casey & Niblett, 'Self-Driving Contracts,' supra note 5, at 22.

use their data to create contractual plug-ins that allocate risks between commercial parties.[51] Commercial arbitrators may use data from their prior decisions to create ex ante arbitration tools. Finally, consumer protection agencies and advocates may develop competing algorithms to offset potential biases.

This raises new questions about the neutrality of the algorithms used in self-driving contract provisions. When both contracting parties are sophisticated, the market will likely do a good job of ensuring neutrality. As we noted in our 2017 piece:

> 'In a well-functioning market, . . . private firms will compete over how well calibrated their ultimate terms are to the parties' objectives . . .'[52]

Still, not all markets are well functioning. And when transactions involve unequal parties, third-party providers may favor sophisticated repeat players.[53]

In those cases, the regulation of the market for providers will be necessary. These concerns are similar to those related to arbitration today. Human arbitrators can be unpredictable or biased and that imposes costs on parties. AI-augmented algorithms can also be unpredictable or have biases that favor one party entrenched in their programming or data.[54]

And so, in the same way that the neutrality of arbitrators can be regulated by legislation or court supervision, the neutrality and competence of the providers of algorithms for self-driving contracts can be regulated. Courts might void contracts that are based on algorithms that are

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[51] *See* Borselli, 'Smart Contracts in Insurance,' supra note 12, at 119.

[52] *See* Casey & Niblett, 'Self-Driving Contracts,' supra note 5, at 27. As we also note, at 27, the market for self-driving contracts is similar to, and takes inspiration from, recent work by Gillian Hadfield, who argues that law is moving toward a private provision of substantive contract law. Hadfield suggests that private firms could fill gaps and compete for the right to arbitrate. Gillian K. Hadfield, *Rules for a Flat World*, supra note 2, at 249-251.

[53] A similar problem exists with rating agencies, *See, e.g.* Robert J. Rhee, 'Incentivizing Credit Rating Agencies under the Issuer Pay Model Through a Mandatory Compensation Competition' (2014) 33 *Banking & Financial Services Policy Report* 11.

[54] Examples of algorithmic bias include studies suggesting that algorithmic risk assessment tools used in the criminal justice system are biased against black defendants. *See* Julia Angwin et al, 'Machine Bias', *ProPublica* (23 May 2016), online: <www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>; *see also* Megan Garcia, 'Racist in the Machine: The Disturbing Implications of Algorithmic Bias' (2016) 33:4 *World Policy Journal* 111; David Danks & Alex John London, 'Algorithmic Bias in Autonomous Systems' (Paper delivered at the Proceedings of the 26th International Joint Conference on Artificial Intelligence, 2017).

intentionally or systematically biased in favor of one party.[55] Likewise, in the same way that arbitration clauses can be struck down as unconscionable if the arbitrator is not neutral, AI in a self-driving contract could be invalidated if it were not neutral.[56]

3.2 Data sources

Additional regulation of how these companies create and use their data may be required. The integrity of the data is important, as are privacy and security issues. There are two broad categories of relevant data: data about the world and data about the parties to the contract.

<u>Training data: data that describe the world</u>

Data about the world is necessary for self-driving contracts to work. Most of the technologies discussed use data about the past to predict future outcomes. Thus, large datasets about the past are necessary.

These datasets may include prior legal decisions when the algorithm is using predictions about what a human referee would do in a future case. In those instances, the AI referee is trying to replicate the decisions of the human referee. That is the objective of the algorithm here. These outcome data are used to find likely ex post decisions and transform those into a contract term.

Alternatively, the datasets may use broad information about events in the world. The parties may not want to replicate a prior judicial outcome. Instead, they may want to achieve a certain real-world outcome.[57] In those cases, the parties use data that measure the objectives that they care about, and the algorithms predict what actions will lead to the realization of those objectives. Such algorithms can improve upon the default rules offered by human referees or address matters where litigation data are sparse.

The integrity and quality of these data sets will determine the quality of the automated contract provisions.[58] Bad data inputs will produce bad outputs. Data can be bad for various reasons, some intentional and some unintentional. Parties may use the best observable proxy for something they wish to measure—for example, using the S&P500 as a metric for the strength of the economy—but such a proxy may not represent

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[55] *See* Marco Rizzi & Natalie Skead, 'Algorithmic Contracts and the Equitable Doctrine of Undue Influence: Adapting Old Rules to a New Legal Landscape' (2020) 14:3 *J of Equity* 301.

[56] When the parties are equally sophisticated, they might agree to use a provider that was not neutral. The court would only invalidate that if the contract promised neutrality. With consumer contracts, the law might require neutrality in all instances.

[57] See, e.g. Williams 'Predictive Contracting', supra note 10.

[58] *See* Michele M. van Eck, 'Disruptive Force of Smart Contracts,' supra note 8, at 28.

the specific movements in the economy that the parties intended. Further, proxies based on indices are subject to the whims and discretion of those constructing the indices.[59] Again, the variation in the indices may not align with the expectations of contracting parties.

Of greater concern, contracting parties can intentionally manipulate algorithms if they can control or influence the data sources. There are a few high-profile examples of data manipulation with simpler non-AI contract formulas. For example, the LIBOR scandal involved financial institutions colluding to submit false data to manipulate the LIBOR index, which was used in their contract formulas.[60] Similarly, in the medical industry, pharmaceutical companies were accused of colluding with third party data providers to manipulate the industry price benchmarks that were used in determining how much insurance companies and the government paid for medications.[61]

These examples suggest that data regulation will be one of the most important government roles in the evolution of self-driving contracts.

<u>Use data: how contract provisions update</u>

Once the data for the underlying algorithms are created, the tailoring of terms will require data about the parties themselves. For example, suppose the parties insert a self-driving notice-period provision into an employment contract. In order to provide a context-specific directive, the algorithm needs to be fed a variety of information about the parties' circumstances.

Some of that information may be personal. For example, one question that would affect the length of a notice period–irrespective of whether the algorithm was based on the current state of the law or on the likely length of time to secure new employment–is whether the employee is suffering from illness or disability. This may raise privacy concerns for individuals. Similarly, with insurance contracts, where the premiums adjust based on data on driving or brushing teeth, privacy advocates have clashed with insurance companies, arguing that the costs of privacy invasions outweigh the benefits.[62]

Firms, too, may not be comfortable sharing proprietary information with third-party algorithm providers. In the example of a bank renewing a

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[59] See*, e.g,* Adriana Z. Robertson, 'The (Mis)Uses of the S&P500' (2021) *University of Toronto Faculty of Law.*

[60] *See* Andrew Verstein, 'Benchmark Manipulation' (2015) 56 *BCLR* 215.

[61] *See* Frederic R Curtiss *et al*, supra note 22.

[62] *See, e.g.* Robson Fletcher, 'New Alberta law would make it easier for insurance companies to track driving habits through your phone' *Canada Broadcasting Corporation* (Nov 26, 2020), available at: https://www.cbc.ca/news/canada/calgary/alberta-bill-41-usage-based-insurance-driver-tracking-1.5810597 .

lease of a large commercial space in a building, the bank may object to revealing sensitive information about their future plans.

There are, of course, incredibly important questions about the security of these data once they are provided to third parties. As with algorithm design, there will likely be a need for some form of regulation of the data. Without sufficient regulation, the reluctance of parties to share private or proprietary information with third party providers could pose a real barrier to the adoption self-driving contracts.[63] Empirical evidence, however, suggests that parties are often willing to waive privacy in exchange for some economic benefit.[64]

3.3 Difficulty in specifying parties' objectives

In our earlier piece on self-driving contracts, we assumed—to make the point—that parties to the contract had a shared objective that they could easily specify. For the most part, we presupposed that that objective was to maximize joint surplus. But specifying these ultimate objectives may be difficult. Parties may have conflicting interests and differing preferences.[65] Indeed, parties may even agree to contractual ambiguity to facilitate agreement when they cannot agree on an ultimate objective.[66]

The parties may also find it difficult to define these objectives in ways that can be cleanly translated for the algorithm. That is, even where both parties share an objective, it may be difficult to specify that objective in a way that is easily measurable by data. The popular literature on AI is replete with examples of reinforcement learning algorithms gone awry because the objective and reward functions were not adequately aligned with what the human designer wished the AI to do.[67]

There is thus a real risk that an algorithm in a self-driving contract provision will implement an objective that doesn't fully align with what the parties actually intended. In this way, AI referees are not so different from human judges!

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[63] *See* Kathryn D Betts & Kyle R Jaep, 'The Dawn of Fully Automated Contract Drafting: Machine Learning Breathes New Life Into a Decades-Old Promise' (2017) 15 *Duke L&TechR* 216 at 229-231.

[64] *See, e.g.,* Sebastian Derikx, Mark de Reuver, & Maarten Krosen, 'Can Privacy Concerns for Insurance of Connected Cars be Compensated?' (2016) 26 *Electronic Markets* 72.

[65] *See* Anthony J. Casey & Anthony Niblett, 'A Framework for the New Personalization of Law' (2019) 86 *UChi LR* 333.

[66] Albert Choi & George Triantis, *Strategic Vagueness in Contract Design: The Case of Corporate Acquisitions* (2010) 119 *Yale LJ* 848.

[67] See Brian Christian, *The Alignment Problem: Machine Learning and Human Values* (Penguin House, 2020); Stuart Russell, *Human Compatible: Artificial Intelligence and the Problem of Control* (Penguin House, 2020).

To the extent that AI algorithms will be able to learn what objective contracting parties wish to achieve, such problems may be capable of being overcome. While this is a real challenge, there are promising signs that it can be met. For example, recent scholarship has shown that AI agents are able to, through machine-learning technology, adopt socially beneficial norms in multi-agent settings.[68] It is plausible that such AI agents will be able to identify the purpose of a relationship and set out obligations by observing past relationships.

4. CONCLUSION

We concluded our 2017 piece by predicting that self-driving contracts will 'be greeted with a healthy mixture of skepticism, trepidation, and fear.'[69] This was certainly our most accurate prediction.

But much of the skepticism is poorly focused. All-knowing, all-seeing general AI machines will perhaps remain in the realm of Hollywood movies and science fiction literature. But AI technologies are advancing. The success stories of AI are primarily narrow applications developed for specific tasks such as parking a car, playing chess, or predicting real estate prices. Machines are outperforming humans in more of these narrow tasks every day. As narrow AI subsumes more tasks previously performed by humans, the technology is becoming more generally applicable and dramatically changing our everyday lives.

The story is the same for the emergence of self-driving contracts. AI provisions that outperform human-drafted content are replacing conventional contracts one provision at a time. The clumsy fixed price term and the simple cost-plus formula will fall by the wayside in favor of more tailored and dynamic automated pricing algorithms. The objectives underpinning a vague standard describing performance may be better captured by an algorithm's better-calibrated and more appropriate micro-directives, providing fewer opportunities for parties to engage in ex post exploitation.

The predictive technology and data underlying these advances will continue to improve – and, piece-by-piece, more and more contractual clauses will become dynamic, self-correcting, and self-driving.

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[68] Eugene Vinitsky *et al*, 'A Learning Agent the Acquires Social Norms from Public Sanctions in Decentralized Multi-Agent Settings', (June 16, 2021), available at: arXiv.org/abs/2106.09012v1.

[69] Casey & Niblett, 'Self-Driving Contracts,' supra note 5, at 31.