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VIEW FROM PRACTICE: Artificial Intelligence and the Fifth Phase of Political Risk Management: An Application to Regulatory Expropriation

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Artificial Intelligence and the Fifth Phase of Political Risk Management: An Application to Regulatory Expropriation

Executive Summary: Using the context of regulatory expropriation, this article extends political risk management theories, forecasting methodologies (employing artificial intelligence, machine learning and data analytics), and human intelligence evaluation tools useful for multinational enterprise (MNE) executives in their planning and decision-making responsibilities. The article identifies three (3) key areas where artificial intelligence will specifically assist managers in analyzing and mitigating risks: 1) Earlier Identification of Risks, 2) Precision in Risk Assessment, and 3) Identification of Unknown Unknown Risk Correlations. These three categories also represent how artificial intelligence and its application to political risk assessment will evolve in the fifth phase of political risk management, and why it is of particular relevance to risks such as regulatory expropriation. Using the example of an oil exploration joint venture between Russian TNK and BP, and reflecting political and public policy indicators of regulatory expropriation, this political risk management framework and its hypothetical development are illustrated.

Keywords: artificial intelligence; foreign direct investment; human intelligence; political risk management; regulatory expropriation

1 Introduction

The term "expropriation" is defined as "the taking by a government of privately owned assets, such as real estate, factories, farms, mines, or oil refineries" [Schaffer et al., (2012). P.24]. "In cases of direct expropriation, there is an open, deliberate and unequivocal intent, as reflected in a formal law or decree or physical act, to deprive the owner of his or her property through the transfer of title or outright seizure" (United Nations Conference on Trade and Development, 2012: 7). Such government action may have a devastating financial impact on multinational enterprises (MNEs) when this "taking" results in a loss of invested capital without adequate compensation (Nikiema, 2013).

For example, in Venezuela, the late President Hugo Chávez was a fierce advocate of state control of strategic sectors, and beginning in 2007 he nationalized steel mills, agribusinesses, and the oil industry (Wyss, 2017). In April 2017, the Venezuelan Judicial Authority seized General Motors (GM) manufacturing facilities, and the company was forced to write off the plant and recognize a $100 million charge against profits (Oxford Analytica, 2018). While unfortunate for MNEs such as GM, after nearly two decades of rhetoric and nationalist initiatives from the Venezuelan government, such potential outcomes would certainly be predictable by international managers using even the most basic of political risk assessment tools. However, while some political risk leading to direct expropriation is easier to identify and account for, other risks that are subtle with indirect outcomes are more challenging to forecast.

As global markets, rules, and regulations have emerged, the risk of direct expropriation has conceivably lessened, or possibly evolved more recently into a specific subset of expropriation: "creeping" expropriation, or "regulatory" expropriation (Newcombe, 2007). Creeping expropriation is "the incremental encroachment on one or more of the ownership rights of a foreign investor that eventually destroys (or nearly destroys) the value of his or her investment or deprives him or her of control over the investment" [United Nations Conference on Trade and Development (2012), P.11]. Such creeping expropriation occurs when a host government imposes regulations that gradually limit the exercise of private ownership rights by the foreign-owned business (Schaffer et al., 2012). This regulatory expropriation, a sub-category of indirect expropriation[1] (Escarcena, 2014; Isakof, 2013), may subject foreign direct investment (FDI) to such things as: discriminatory taxes, domestic government controls over management of the foreign-owned firm, price controls, mandatory employment of nationals, cancellation of government-issued business licenses, and restrictions on currency convertibility (Schaffer, et al., 2012), among others. While Rice and Zegart [(2018a), p.132] believe that “expropriating leaders are far less common than they used to be”, it does not mean that this expropriation is not being undertaken utilizing more subtle regulatory actions.

As MNE interest in emerging markets has dramatically increased in the 21st century, host countries have learned, “that more value can be extracted from foreign enterprises through the more subtle instrument of regulatory control rather than outright seizures”, says George Chifor [Henisz and Zeiner, (2010), p.90]. Today’s MNE, operating under the global rules established by the World Trade Organization, is more likely to encounter regulatory expropriation that is subtle, indirect, incremental, and thus more challenging to identify and manage effectively than direct expropriation, a blunt, direct, and obvious action perpetrated by national governments against foreign-owned companies in the 20th century. Consequently, as the current environment brings forth a new era of political risk, it has also delivered an increasingly sophisticated technology to help with a new phase of risk assessment: artificial intelligence.

Regulations that result in the *de facto* expropriation of property deny an owner the ability to use or sell property, or otherwise dramatically limit its use, therefore reducing its market value (OECD, 2018). An example of regulatory expropriation occurred in 2010, when the Arctic joint venture between Russian TNK[2] and BP came under severe Russian government regulatory pressure after the joint venture developed conflicts with national state-owned oil and gas giant Gazprom over issues concerning pipeline access and development strategy (Schaffer et al., 2012). In this case, Russian government regulators insisted on a northerly route for the pipeline to pass other, smaller gas fields that would otherwise be uneconomical to develop, and made clear that Gazprom, and not the TNK-BP joint venture, would decide when to build that pipeline

(Kramer, 2010). In addition, the Russian government later revoked other foreign MNE oil permits, citing environmental regulatory concerns (Schaffer et al., 2012).

While regulatory expropriation is a recognized political risk by MNEs and their stakeholders, the challenge for MNE executives is recognizing when this government activity is actually occurring in a host country – and if it is applied to all foreign MNEs or focused on certain MNEs. For MNEs, regulatory expropriation affects several aspects of foreign direct investment (FDI) and executive decision-making and it needs recognition as an important ingredient of political risk assessment factored into entry and exit of markets, and timing and mode of entry or exit. In addition to state-of-the-art developments in the human intelligence aspects of political risk assessment, in this paper we formally introduce data analytics, machine learning, and artificial intelligence, as integral to the next phase in the evolution of political risk management.

Political risk management has largely undergone four phases of incremental evolution (Jarvis and Griffiths 2007a; Jarvis 2008) and, at the start of the 21st century, there is potentially a departure from the fourth phase. Here, despite sophisticated analytical tools and systems, uncertainty may still be so hard to envision it cannot be reasonably incorporated into probabilistic predictions and used in models (Makridakis, Hogarth and Gaba, 2009) – built with the cognitive limitations of the humans governing them. Political risk management will see an evolution toward artificial intelligence where machines at first need human input for crafting predictions, then make decisions on their own in the near future, and eventually will not suffer from the limitations of human intelligence in trying to incorporate uncertainty.

According to Rice and Zegart [(2018a), p.132] "21st century political risk is essentially the probability that a *political action* will significantly affect their business – whether positively or negatively. “They go beyond the usual locales – nation’s capitals, military barracks, and political party headquarters – as such political activities are “almost anywhere – inside homes, on the streets, and in the cloud, in chat rooms, dorm rooms, and bathrooms; in neighborhood bars and summit sidebars [Rice and Zegart, (2018b), p.7].” This is where Rice and Zegart’s broader concept of “political action” is integral to effective political risk analysis. By tapping into these “private” sources of real-time opinion, i.e., “human intelligence” acquiring, allows corporate social scientists to offer their nuanced analysis of a possible competitive edge needed to effectively manage the possible impact of these global political actors in a complex business environment.

Following this brief introduction to expropriation and regulatory expropriation, this article will first, review the state of the field of political risk analysis and management – with a focus on expropriation. Second, we extend political risk management theories, forecasting methodologies, and evaluation tools to incorporate the vexing problem of regulatory expropriation into a new strategic political risk framework employing data analytics, machine learning, and artificial intelligence (AI), all useful for MNE managers. Third, taking this proposed political risk management framework, we explore its hypothetical development using the above-mentioned venture between Russian TNK and BP reflecting political and public policy indicators of regulatory expropriation. Lastly, we discuss the importance of this fifth phase of political risk management, and how it will provide heretofore unavailable benefits for MNE executives who need to assess nuanced threats and opportunities in the global political economy.

2 Political Risk Analysis and Management: State of the Field

Today, most businesses recognize that political actions and decisions have major implications for commercial operations in the global environment (Fagersten, 2015). For example, Oxford

Analytica (2018), in a recent survey on managing global business political risk, reported 60 percent of business respondents reporting that political risk levels had increased since 2017, 75 percent avoided investing in a country because of political risk concerns, and 68 percent expressed country specific political risk concerns. Overall, 35 percent of respondents replied that they suffered political risk-related losses in recent years, with 43 percent reporting such losses exceeding $100 million (Oxford Analytica, 2018).

Political risk, as confronted by MNEs, is similar to “macroeconomic risks” and “policy risks” identified under Ghoshal’s (1987) risk typology framework. It can be defined as “the risk of strategic, financial, or personal loss for a firm because of such nonmarket factors as macroeconomic and social policies (fiscal, monetary, trade, investment industrial, income, labor, and developmental), or events related to political instability (terrorism, riots, coups, civil war, and insurrection)” [Kennedy (1988), p. 27]. Also, as Bremmer and Keat [(2010), p.21] point out, “[U]nlike financial, economic, or environmental risks, political risks are usually generated by individuals, people with particular and identifiable sets of motivations and limitations.” While the field of political risk management has traditionally focused on analyzing uncertainties in emerging economies, recent political events in the global political economy have broadened its scope to include the developed economies and established liberal democracies (Campisi, 2016).

For the purposes of political risk management, political risk can be further bifurcated into *macro-level* political risk and *micro-level* political risk. Macro-political risk analysis evaluates non-project specific risks that affect all levels of stakeholders in a country (Alon and McKee, 1999). Such macro-political risks include regulatory changes, endemic corruption, government leadership turnover, and national credit defaults. Micro-political risk analysis evaluates project-specific risks affecting a business endeavor (Alon, Gurumoorthy, Mitchell, and Steen, 2006).

Such micro-political risks may include business project-specific government reviews, the selection of questionable, host country business partners, and the potential for expropriation or nationalization of a project or assets. "Historically, some of the business world's best political risk analysis has come from multinational enterprises, like Royal Dutch Shell and American International Group (AIG), that have entire departments dedicated to the subject" [Bremmer, (2005), p.52].

From the vantage point of understanding its modern evolution, political risk analysis has gone through four distinct phases (Jarvis and Griffiths, 2007a; Jarvis, 2008) (see Figure 1 below for detailed descriptions). The first three phases of political risk analysis are indicative of late 20th century development in the field. The fourth phase, however, reflects a critical (for MNE executives) 21st century approach to political risk analysis designed to link institutional and contextual characteristics to the probability of risk events, and thereby warn decision-makers (in NGOs and international aid agencies) of impending humanitarian crises (Jarvis and Griffith, 2007). This fourth phase methodologic approach is readily transferable to MNEs, that are also vulnerable to such impending macro-environmental events affecting their operations and influencing managerial responses in these locales.

[Insert Figure 1]

While 'Phase Four' is largely where the field remains today, the early warning systems (EWSs) are made increasingly sophisticated though advances in technology and data availability. Business Intelligence (BI) tools have proven vital to decision makers in support of EWSs across a wide range of industries and applications (e.g., insurance, real estate, macroeconomic (Wu, Chen, and Olsen, 2014). Limitations in data availability still remain a major issue when trying to accurately assess political risk; however, perhaps a greater obstacle standing in the way of moving to the next 'phase' of analysis is knowing what data to analyze – i.e., 'the knowing what to look for' is a greater issue than the 'not being able to find it' one.

Rice and Zegart (2018b) view three megatrends transforming the political risk landscape over the last thirty years: first, dramatic changes in geopolitics since the end of the Cold War, second, supply chain innovations, and third, the information technology revolution (Rice and Zegart, 2018b). Furthermore, Rice and Zegart (2018b) identify a political risk management framework that requires four core competencies to be effective and, at each step in this political risk management framework, they identify three guiding questions that organizational members can ask to address the most important issues):

- Understanding Risks (What is my organization's political risk appetite? Is there a shared understanding of our risk appetite? How can we reduce blind spots?)
- Analyzing Risks (How can we get good information about the political risks we face? How can we ensure rigorous analysis? How can we integrate political risk analysis into business decisions?)
- Mitigating Risks (How can we reduce exposure to the political risks we have identified? Do we have a good system and team in place for timely warning and action? How can we limit the damage when something bad happens?)
- Responding to Crises (Are capitalizing on near misses? Are we reacting effectively to crises? Are we developing mechanisms for continuous learning?)

Yet, while many researchers use financial crises (e.g., currency, sovereign debt, equity) to bring attention to deficiencies in risk management models (Jorion, 2009), others introduce new indicators for EWSs (Castell and Dacuycuy, 2009; Krstevska, 2012), thus highlighting the incremental nature of improvements in the field of risk management. Furthermore, examining the development of EWSs applied to one field may also lead to innovations in other fields. For instance, on January 9, 2020, the World Health Organization (WHO) first reported a flu-like outbreak and pneumonia symptoms in China's Wuhan province, with the US Centers for Disease Control and Prevention (CDC) reporting it days earlier on January 6th (Niiler, 2020). However, as Eric Niiler (2020) reported online in *Wired*, BlueDot, a Toronto-based health monitoring platform founded in 2014 that uses AI-driven algorithms, "had beaten them both to the punch, sending word of the outbreak to its customers on December 31." In this article, BlueDot's founder Kamran Khan highlights the fact that when there is an outbreak, speed matters, and Chinese officials are "tight-lipped" and "do not have a good track record of sharing information" (Niiler, 2020). While there are still challenges, this company and example highlight the fact that governments may not provide information at all, or in a timely fashion, and that AI-driven algorithms can often discover trends and make predictions faster.

Many attempts at forecasting risk focus on models where "uncertainty can be reasonably incorporated into probabilistic predictions" [Makridakis, Hogarth and Gaba (2009) p. 795] and not ones where the uncertainty is so hard to envision it cannot be modeled (Makridakis, Hogarth and Gaba, 2009). BlueDot's founder stated, "We can pick up news of possible outbreaks, little murmurs or forums or blogs of indications of some kind of unusual events going on" (Niiler, 2020). As fears of the spreading virus increased, so did the international response that caused three major US airlines to cancel flights to the Chinese mainland, sending stocks tumbling, and the issuance of a travel ban suspending entry for anyone who has recently traveled to China (Chokshi, 2020). So, while the impact of the pandemic on business is felt nearly immediately, such events are also political in nature and the consequences of various governmental responses will be felt in the coming years. This draws attention to the possibility that AI-driven algorithms may be designed with one purpose in mind (e.g., community health risk monitoring), but have several applications (e.g., political and financial risk management). In this example, the concerns and utility of such predictions are also discussed in terms of reliability of using social media information for data mining – without human oversight or a healthy skepticism of what predictions and patterns emerge. Fine tuning analytics in concert with human oversight is still necessary for big decisions.

The fifth phase of political risk analysis, building on a combination of data analytics, artificial intelligence, and human intelligence, will be able to combine complex qualitative models and scenarios with real-time big data from various social media platforms. Rice and Zegart's (2018) political risk management framework is specifically relevant to this "Fifth Phase of Political Risk Analysis" for two competencies: analyzing risks and mitigating risks. The analyzing risks competency is based on a rigorous foundation of cloud computing, data analytics and enhanced AI technology. The mitigating risks competency is based on a complimentary foundation of "human intelligence", steeped in the knowledge and insights provided by political scientists, political economists, sociologists, and country-specific analysts. This fifth phase of political risk analysis will be the next generation of *strategic* political risk management, and a valuable mechanism for uncovering the risks of regulatory expropriation for MNEs in the 21st century.

3 Strategic Political Risk Management: Data Analytics, Machine Learning and Artificial Intelligence

The "Fifth Phase of Political Risk Analysis" is predicated on developments in "machine learning." According to Fagella (2019):

> Machine learning is the science of getting computers to learn and act like humans do, and improve their learning over time in autonomous fashion, by feeding them data and information in the form of observations and real-world interactions.

Machine learning involves statistical predictions based on unanticipated correlations to solve problems. Recent advances in machine learning have transformed how we can utilize dynamic, probabilistic models to predict instead of utilizing rule-based, static logic. The output of machine learning ("the prediction") is "a key component of intelligence, the prediction accuracy improves by learning, and the high prediction accuracy often enables machines to perform tasks that, until now, were associated with human intelligence, such as object identification [Agrawal, Gans and Goldfarb, (2018), p.38]." Thus, at this level of prediction accuracy, one can refer to it as "artificial intelligence." Artificial intelligence (AI) is a system that makes autonomous decisions. According to Webb [(2019), p.13]: "The tasks AI performs duplicate or mimic acts of human intelligence, like recognizing sounds and objects, solving problems, understanding language, and using strategy to meet goals."

There are three phases in the evolution of AI systems (Webb, 2019). First, there is *artificial narrow intelligence* (ANI). The ANI systems, which have proliferated over the last decade, are presently capable of performing a singular task at the same level or better than humans (Webb, 2019). Second, there are *artificial general intelligence* (AGI) systems which will perform broader cognitive tasks, e.g., reason, solve problems, think in abstraction,and make choices, as these systems are designed to think like humans (Webb, 2019). The AGI systems are considered "near future", i.e., implementable within the next ten to twenty years. Third, are *artificial superintelligence* (ASI) systems. According to Webb [(2019), p.144]: "ASI systems range from being slightly more capable at performing human cognitive tasks than we are to AIs that are literally trillions of times generally smarter than humans in every way." The ASI systems are considered "distant future", i.e., implementable beyond the next two decades. For the purpose of developing the next phase of political risk management, AGI systems will be our focus for applications to impending regulatory expropriation.

There are four categories for understanding the conditions under which prediction machines succeed or falter [Agrawal, Gans and Goldfarb, (2018), see pp.59-65]. The first category is *known knowns*, where there is an abundance of rich data allowing for good predictions. The second category is *known unknowns*, where there is little data, so predictions are difficult. The third category, *unknown unknowns*, include those events not captured by past experiences or what is present in the data but are nonetheless possible, so prediction is also difficult. The fourth category, *unknown knowns*, is when an association that appears to be strong in the past is the result of some unknown or unobserved factor that changes over time and makes predictions that were believed to be reliable, nevertheless unreliable. Today, the *known known* is where the current generation of machine intellignce is successfully employed, and results in ANI systems that have the potential to assist in effective political risk management – in this case, predicting regulatory expropriation.

However, the next two decades should see a rise in AGI use and capability in political risk management, at first requiring greater levels of human oversight and intelligence and then, gradually as the machine learning becomes more reliable and accurate, human intelligence will not only be less important to the process, but may actually interfere with it. While *known unknowns* and limited data make machine learning difficult now, AGI systems may be capable of finding alternative sources of data or using the absence of data as information. These transitions in the development and use of AI are not unlike efforts to bridge the gap between applied and theoretical physics. Indeed, with physics "the unkown unknowns will reveal themselves to those who study hard, who can see obscure connections, indulge in lateral thinking and who might even just get lucky and find some serendipity!" [Whitehead, (2016), p. 21], which sounds just like what AGI systems may eventually do. Similarly to *unknown knowns* in scientific fields, new discoveries may also cause us to reevaluate that which we thought we new.

The fifth phase of political risk management will be predicated on AI developments in *cognitive analytics*. Cognitive analytics "applies intelligent technologies to bring all of these data sources within reach of analytics processes for decision-making and business intelligence (Expert System, 2016)." The three components that make up cognitive analytics consist of data management, natural language processing, and digital analytics and delivery (see Figure 2 below). *Data management* is "an administrative process that includes acquiring, validating, storing, protecting, and processing required data to ensure the accessibility, reliability, and timeliness of the data for its users" (Galletto, 2016), and is utilized along with the mining of untapped data sources, which will drive predictive and prescriptive insights. The use of "cloud computing" is integral to effective data management. *Natural language processing* is "a branch of artificial intelligence that deals with the interaction between computers and humans using the natural language (Garbade, 2018)." By relying on machine learning, natural language processing will "read, decipher, understand, and make sense of the human languages in a manner that is valuable (Garbade, 2018)." *Data analytics and delivery* involves the use of cloud technologies and process automation that enables on-demand customized analytics and real-time collaboration to support key business decisions (Intel, 2015).

[Insert Figure 2]

The McKinsey Global Institute, in its discussion paper addressing how companies will decide on how to optimize for AI, argue that [Bughin, et al., (2018), p.46]:

> The productivity dividend of AI probably will not materialize immediately – its impact is likely to build up at an accelerated pace over time, and therefore the benefits of initial investment may not be visible in the short term. Patience and long-term strategic thinking will be required.

The preceding statement aptly describes the later stage of ANI development. i.e., involving a specific, bounded parameter of analytic capability, and the fifth phase of political risk analysis. Over the last five years, there have been a few examples of private companies who have been pathfinders in combining AI, data analytics, and global political risk analysis. For example, Predata, founded in 2015 (Nanalyze, 2019), uses machine language algorithms to curate anonymized online metadata, applies machine learning algorithms to the collected data over time and across various countries, and then take predictive signals to quantify identified potential geopolitical risks (Predata, 2020). The Predata approach focuses on patterns of behavior, as they replicate more reliably than in the data itself (Predata, 2020). Moreover, Predata (2020) Focus offers a geopolitical risk insights through a dashboard view.

Another technology startup, GeoQuant has developed high-frequency, AI-driven political risk intelligence measures that analyze and forecast political risks to MNEs in real time (GeoQuant, 2017). GeoQuant developed the world's first benchmark measures for geopolitical risk using both structured and unstructured data (Nanalyze, 2019). GeoQuant's structured data is acquired from 250 variables (many of them political factors previously thought unmeasurable) drawn from the company's proprietary, fundamental model of political risk (based on measuring 22 fundamentals of politics, drawn from political science/political economy literature) and credible, country-level databases maintained by multilateral institutions, NGOs, governments, and social scientists, with historical data going back to 2009 (GeoQuant, 2017; Nanalyze, 2019).

While the above mentioned data analytics and enhanced AI technology are critical to the development of the "Fifth Phase of Political Risk Management", the human intelligence aspect will be of similar importance in developing accurate geopolitical risk models, and to accurately dicern subtle changes in areas difficult to monitor and measure, e.g., country-based, regulatory expropriation trends. As can be seen in Figure 3 below, the Observe ("Decide what objects to capture content – and capture content."), Orient ("What does the content mean?"), Decide ("What should we do about it?"), and Act ("Implement the decision.") Decision Process, developed by John Boyd, is directly applicable to the AI decision-making process (Carone, 2019). As Carone [(2019), p.12] notes, the "Orient" stage in this process is what AI and machine learning cannot do well and requires a knowledgable human being to analyze complex meaning. Therefore, state-of-the-art approaches to human intelligence, political risk management techniques, and approaches will need to be integrated into these new disruptive technologies.

[Insert Figure 3]

4 The Fifth Phase of Political Risk Management Framework

In the fifth phase of the political risk management framework, involving data analytics, machine learning, and ANI, combined with enhanced human intelligence, an improved modelling of the regulatory expropriation phenomenon, will become available for MNE business decision-making (see Figure 4 below). Regulatory expropriation is subtle, indirect, and incremental, and thus more challenging to identify and be managed by the MNE effectively.

[Insert Figure 4]

The fifth phase will be an evolutionary phase where ANI systems, which rely almost entirely on human intelligence for algorithm programming, development, and oversight, transition to AGI systems where the relationship with human intelligence is more complementary. Naturally, as machine learning is applied to more cognitive reasoning and decision making, similar to human intelligence, political risk management models and other AI assisted decision making will likely require a great deal more high-level human intelligence interaction. For instance, this might at first resemble a promising researcher both collaborating with, and having his or her work checked by, a more seasoned and experienced researcher.

This collaborative process yields two beneficial outcomes despite its seeming redundancy. First, having humans check and oversee the decisions and outcomes of the AGI systems will foster a belief and assurance of their reliability as a foundation for more automated system (AS) decision making. Second, the AGI systems are likely to, both initially and as they become more sophisticated, produce unexpected results that cause further evolutions and developmental breakthroughs in the AGI programs and the risk management models they support. Eventually, as the AGI becomes more refined and reliable, complementing human intelligence will increasingly become unnecessary. Building on models of contemporary political risk management, we will illustrate how to apply techniques that use ANI systems and human intelligence in a complementary fashion, building dynamic capabilities (not static ones), that will eventually be considered AGI-level technology.

TNK-BP

The TNK-BP joint venture could be thought of as the perfect reason for a joint venture or a perfect storm of challenges waiting to happen. TNK (Tyumen Oil) was controlled by the AAR (Alfa Group, Access Industries, and Renova) consortium, which is respectively owned by three

Russian oligarchs (Mikhail Friedman, Len Blavatnik, and Victor Vekselberg), whereas BP was a western firm and the world's third-largest oil company, when the roughly $7 billion merger was announced in 2003 (Kyj and Kyj, 2010). At the time, BP was seeking to expand its assets and options internationally and this occurred during a period of consolidation in the oil industry. TNK, on the other hand, hoped to benefit from the technical expertise of BP allowing for further expansion of fields and gains in efficiencies that would likely emerge (Kyj and Kyj, 2010). Tyumen also had shared oil field rights with Sidanko, another Russian company and project in which BP had purchased a 10% stake (Kyj and Kyj, 2010). Ironically, BP may have seen this as an opportunity to reduce political risk by partnering with two Russian companies, but may have missed the fact the Tyumen had been sued by a Canadian company for failing to meet its obligations in another JV (Feils and Sabac, 2010).

While in theory the JV was set to be an equal partnership, both TNK and BP having 50% ownership and each appointing 5 members to the board of directors, each may have had divergent needs and goals (Kyj and Kyj, 2010). Of course, BP wanted to gain access to Russian oil fields and had longer-term development aspirations that required more investment and slower returns and was even willing to assume some of the liabilities of TNK companies associated with environmental remediation from previous issues, but TNK had a shorter-term profit horizon (Kyj and Kyj, 2010) and goals for the venture. Ironically, BP's own environmental issues with the Macondo (Prospect), Gulf of Mexico oil spill in 2010, required roughly $30 billion cash for settlements and pushed TNK-BP to buy BP assets in Venezuela and Vietnam, for market expansion (BP/TNK-BP, 2010). This at a time when TNK was accusing BP of running the JV as a subsidiary and where TNK-BP, found its venture facing increasing pressure from the Russian government. TNK-BP had come under investigation and inspections from a Russian environmental agency, for issues related to past infractions of other companies, demands for back taxes, and the sudden withdrawal of visas for BP technical experts under the guise that they were compensated unfairly compared to nationals (Kyj and Kyj, 2010) – the beginnings of regulatory expropriation.

For example, the earlier mentioned regulatory expropriation activities against the joint venture between Russian TNK and BP, which came under Russian government regulatory pressure when regulators insisted on a northerly route to pass and smaller gas fields that would otherwise be uneconomical to develop, made clear that Gazprom, and not the BP-Gazprom joint venture, would decide when to build that pipeline (Kramer, 2010). In essence, the Russian government wanted greater control over the venture, more of the profits, and with respect to the pipeline, unnecessary infrastructural development. In addition, the Russian government later revoked other foreign MNE oil permits, citing environmental regulatory concerns (Schaffer et al., 2012). Under the "Fifth Phase of the Political Risk Management Framework", there would be two integrated, complementary approaches to gauging political risk analysis pertaining to MNE regulatory expropriation in this proposed Russian gas pipeline development project.

The Russian regulators insistence on a northerly route for the TNK-BP joint venture is an example of a "direct" data point (the "mitigating risks competency" aspects) – found in preliminary government statements and formal correspondence to the companies, for example – which will be evaluated directly by human intelligence, and not as reliant on ANI for political risk assessment. However, the revocation of other foreign MNE oil permits would not necessarily be as "direct", since these decisions would be based on broad "environmental concerns." These "indirect" data points – the "analyzing risks competency" aspects – would require a comprehensive assessment of what these environmental concerns were and whether an oil/gas MNE's building permit was in violation of these "environmental concerns." Further, the revocation of visas and demands for back taxes would be more direct data points, but bad press of the intent of BP in the TNK-BP venture (perhaps in press from the oligarchs running TNK) and issues surrounding past environmental infractions in oil fields before the TNK-BP venture would be indirect.

Such an "analyzing risks competency" assessment may require an extensive review of government environmental regulations, comparisons among permits granted, an evaluation of previous permits that were pulled by the Russian government, formal assessments of written decisions made by the Russian government, etc. An ANI system will be able to perform this evaluation utilizing cognitive analytics (specifically natural language processing technology) and through increased exposure to data points and machine learning experience, therefore learning to recognize patterns of relevant social and political movements, public policy discussions and judicial decision indicators that would help build models for increasing predictive probabilities for specific regulatory expropriation outcomes. This, in turn, will assist the human intelligence specialist to further identify what these probability outcomes mean, and adjust these predicative probabilities, by further refining these knowledge inputs to be included in policy options for MNE executive decision-making. Eventually, perhaps in 10 to 20 years, AGI technologies will be able to connect and create patterns that precede the direct and indirect data points that more easily captured and processed by ANI and human intelligence currently, but as part of an enhanced EWI system that exceeds the current limitations of ANI and human intelligence.

This political risk management process could begin by exploring several aspects affiliated with such incidences of regulatory expropriation and follow similar suggestions common to the risk assessment process **(**as discussed by Rice and Zegart (2018b)**)**. Key elements such as determining what value exists in a company, what could affect its ability to be created, and the likelihood of such events happening are all important steppingstones for incorporating AI into political risk management. In the case of BP investing in the Kovykta natural gas field in Siberia (Kramer, 2010), executives would have known that the value of the acquisition is determined by their ability to produce the bulk of the natural gas that existed there—and efficiently transport it to China for sale. So, effective risk management teams would have assessed that value and then examined aspects that could disrupt their ability to extract that value. In this case, energy politics came into play where Russia wanted more control, a greater share of the profits, and tried to also force, by means of developing an indirect pipeline route, BP to invest in accessing other less profitable oil fields (Kramer, 2010), essentially altering the value proposition.

This outcome is truly the departure point for evolutionary machine learning. Indeed, there are several things that could have occurred and did occur that led to this outcome; but ANI technology will need to be developed with human intelligence to address "why" they occurred before it approximates AGI and can be autonomously deployed in political risk management. For example, BP's initial investment occurred in the mid-1990s and they started to confront project development obstacles during the late 1990s and early 2000s (Kramer, 2010). A machine might have trouble making connections that seem readily apparent to human intelligence in relation to the energy politics that would later occur to generate this regulatory expropriation. A human with even a cursory understanding of this period of time could suggest that this period of transition between the former Soviet Union and Russia, especially where Boris Yeltsin was later regarded as selling large state-owned companies to insiders in what was called the "loans for shares" scheme to gain monies needed to win reelection in 1996. Naturally, this might have served as a pretext for political attacks targeting businesses, especially foreign ones, for having *robbed* the country of its resources and serve as justification for a renegotiation of terms – a perfect sort of energy politics for a newly-elected Vladimir Putin.

5 Discussion and Implications

Rice and Zegart's (2018b) identification of 'risk appetite' as part of understanding political risk management is consequential for managers and of particular relevance to the fifth phase in this field. Ultimately, there are three (3) key areas where artificial intelligence will assist managers in analyzing and mitigating risks: 1) Earlier Identification of Risks, 2) Precision in Risk Assessment, and 3) Identification of Unknown Unknown Risk Correlations. These three categories also represent how artificial intelligence and its application to political risk assessment will evolve in the fifth phase and why it is of particular relevance to risks such as regulatory expropriation.

Earlier Identification of Risks will provide managers more time, more information, and more options to consider. Artificial Narrow Intelligence (ANI) requires a great deal more human input and is the state of the field early in the fifth phase. Many broad macroeconomic and policy risks, and their antecedents, have already been identified by managers within MNEs. These known knowns are incrementally adjusted with human input into risk assessment models and where the human-machine interaction continuously develop and refine algorithms to enhance early warning systems. For instance, there are many known antecedents to macro-level fiscal or monetary policy change, and risk issues with income and labor are often tied to civil war and insurrection directly. These correlations can be programmed into algorithms by humans and automated by machines that assist managers in identifying risks earlier with each iteration. But, in seeking less incremental, and instead more revolutionary breakthroughs, humans will begin exploring unknown knowns – they know there is likely some unobserved factor at work. Thus, they ask machines to look for unknown patterns and indirect correlations that come before what they know to be correlated. Managers that seek the advantages of earlier identification of risk will be the catalysts, pushing the use of artificial intelligence to find unknown relationships that can provide an edge, rather than accepting its status quo application. Naturally, the 'push' for innovations will come from companies and industries that stand to benefit the most from earlier identification of risks and, therefore, the evolution may not be uniform across industries or businesses. Environmental issues are always a concern for oil companies and partnerships for market expansion a necessary evil, ANI systems as they progress toward AGI would have perhaps not missed the previous environmental issues the TNK had and the current legal issues they faced. Both would have been considered important to humans for political risk, but somehow escaped or did not garner sufficient attention as possible indirect issues that would emerge later.

Precision in Risk Assessment is a critical component to understanding risk appetite and the decision to internalize or externalize—this is tied to macro-level and micro-level political risk—the majority of this effort and associated resources and costs. Macro-political risks, including regulatory changes (e.g., monetary and fiscal policies), national credit defaults, corruption in government, and leadership turnover (Alon and McKee, 1999), have broader contemporary understanding (i.e., well-developed risk assessment models) and applicability for governments, NGOs, and across industries. Consequently, there is likely to be greater demand, and a quicker transition from ANI systems requiring human interaction, to AGI systems where human input gives way to automated discovery and decision-making with human oversight (see Figure 5 below). Since these types of macro-political risk have broader applicability, the need to internalize this work is also diminished. Micro-political risks, on the other hand, have project-specific risks affecting certain business endeavors (Alon, Gurumoorthy, Mitchell, and Steen, 2006). As businesses may have concerns that require precise political risk assessment related to the endeavor, perhaps even proprietary, the evolution of AGI systems to assist firm-specific needs will occur more slowly. What is of consequence with TNK-BP is whether this particular venture was subject to more or less political risk in relationship to TNK and the Russian oligarchs than perhaps other ventures might have been, either due to prior issues or the political weight of the actors. Perhaps the areas in which the venture sought to benefit or even the industry itself was more subject to risk, certainly the volatility of Russia was known to many MNEs at the time, but AGI systems may allow more precision by industries or even ventures that have particular partners and target areas for development of projects.

[Insert Figure 5]

This may also require an internalization of such activities and while such companies as AIG and Royal Dutch Shell may have some of the world's best political risk assessment through their own dedicated departments (Bremmer, 2005), others do not. Accordingly, businesses that seek the precise political risk assessment that may be afforded by innovations in AI, must decide whether to develop or enhance their own departments internally, or try to balance the protection of proprietary information with the desire to externalize this activity. The externalization process may warrant some additional legal concerns and perhaps a highly dedicated client server from any consulting firm that is hired. Naturally, as the application and use of ANI systems for greater and greater types of analysis, machine learning will accelerate until AGI systems are available for both macro and micro-level risk analysis.

Identification of Unknown Unknown Risk Correlations is the eventuality of ANI sophistication in the precision analysis that leads to the development and deployment of AGI systems. In this latter stage of the fifth phase of political risk assessment, humans will no longer interact with machines in an effort to direct them to search for information, rather the machines will begin to search for patterns and causal correlations that humans don't know that they don't know. At this point, humans will serve largely in a supervisory role, where automating minor decisions may be routine, but major decisions and analysis will still be in human hands. With the acceleration of breakthroughs in AI, this point where AGI systems start leaning away from the limitations of humans, and toward the capabilities of artificial super intelligence (ASI), may be brief or prolonged. The length of this transitional phase will likely be determined by the pace of technological innovation and moderated by a host of business, societal, and ethical concerns. This is where analysis of things such as regulatory expropriation, that is very subtle and difficult for humans to predict, may be well supported.

The TNK-BP joint venture would have benefitted from enhanced political risk management models that incorporated ANI, machine learning, and data analytics. Firstly, coupled with human intelligence, ANI systems might be developed to look for political trends in media or other outlets that would suggest the risk of regulatory expropriation was rising, of direct benefit to BP executives and influencing further decisions regarding investment or disinvestment. Of course, this would be in the early stages where the data would more likely resemble *known knowns* and the programming would rely more heavily on human assumptions and intelligence. Secondly, as the technology evolves and machine learning is improved, ANI systems could give way to AGI ones where *unknown unknowns* and *known unknowns,* things we as humans don't know that we don't know—and things we thought we knew but really didn't, make ultra-sophisticated political risk models for EWS's the norm (of even greater value for improving BP managerial decision-making). Stated another way, the initial assumptions and connections a human might make about why regulatory expropriation has occurred years later could be completely wrong or more readily identified by factors only identifiable to AI systems. The AGI systems could have been monitoring press and political changes and also capturing ambitions of interested parties in the TNK-BP venture that are all seemingly unrelated to how humans perceive and anticipate risks but captured by AGI systems. Thus, allowing for probabilities of outcomes that could incorporate *what-if* scenarios for things, such as the Macondo Project oil spill in the Gulf of Mexico, and how this might lead to changes in assets sold and sought by parties, as well as how this affects strategic direction.

Lastly, the "Fifth Phase of Political Risk Management" will provide the next level of analytic insights for MNE management. The powerful tools inherent in ANI (and later AGI) utilizing state-of-the art machine learning and enhanced data analytics, complemented by the next generation of political risk management frameworks, approaches and concepts applied to human intelligence, will offer MNEs the opportunity to seriously address the heretofore challenging issue of being confronted by national governments (such as with the Russian government) with regulatory expropriation (as in the case of TNK-BP). In the case of AGI, the use of high-level human intelligence (involving subject matter experts) will further enhance the nuances found in the social, political, and economic trends impacting the political risk management models. This earlier recognition of these often subtle, incremental changes in their operating environments at an earlier stage, offers MNE executives a wider array of strategic options to embrace, thus helping them to mitigate the negative impacts on their companies. For example, it is essential for executives to consider a wider array of political actors who express opinions on issues relevant to MNEs, and who transmit these opinions on their personal electronic devices in "real time."

However, it should be recognized that while the development of AGI technologies may take 10 to 20 years and be incremental, the timeline in development of AI technologies can be described as long periods of incremental development coupled with a few giant leaps forward (Lee, 2018). While some companies may choose to be at the forefront of applying artificial intelligence in their political risk management, investments in such technology could be rendered obsolete by disruptive innovations and breakthroughs. Yet such organizational investments will, from a benefit-cost perspective, more likely result in critical dividends for MNEs over the longer term. In conclusion, given the increasingly nationalistic operating environment for MNEs, the use of "stealthy" approaches – such as regulatory expropriation – to reducing business opportunities for non-domestic competitors will become more prolific, and therefore the need for more powerful political risk analysis tools and approaches of greater MNE strategic importance.

Endnotes

1 “Indirect expropriation involves total or near-total deprivation of an investment but without a formal transfer of title or outright seizure” (United Nations Conference on Trade and Development, 2012: 7).

2 The TNK-BP was an integrated oil company with oil exploration one of the joint venture’s activities. TNK was controlled by three Russian oligarchs who owned a financial entity called AAR, which contributed 50% of TNK to the TNK-BP joint venture. [The authors wish to acknowledge a reviewer who provided them with this information.]

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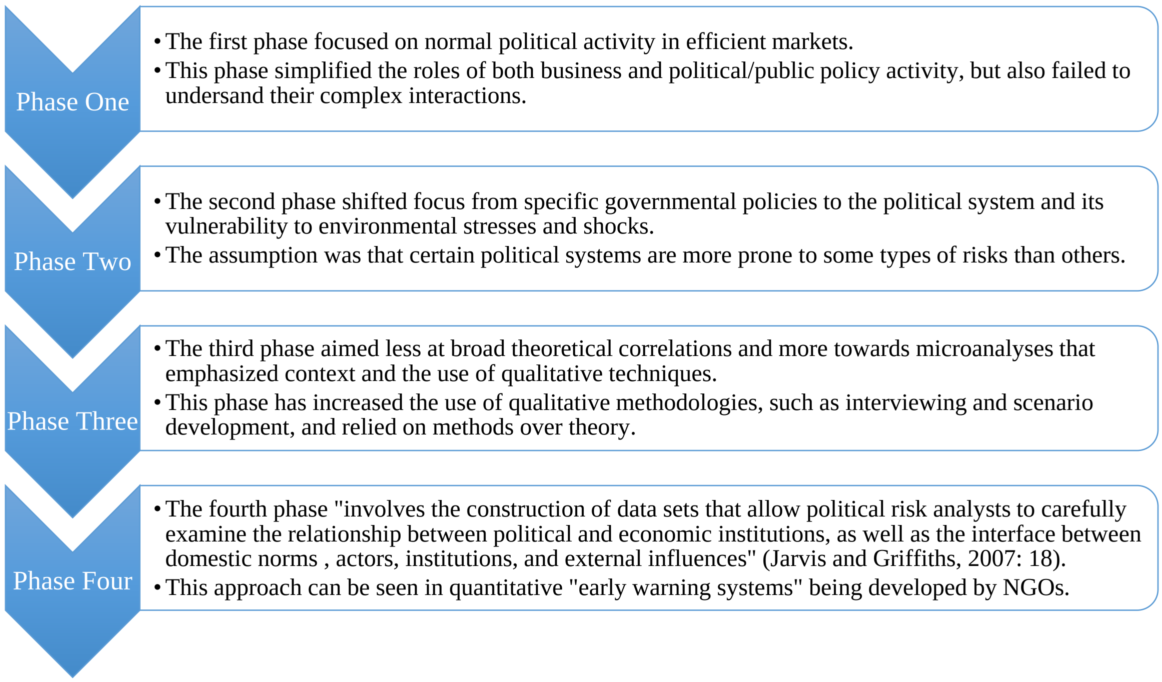
Figure 1

The Four Phases of Political Risk Analysis



Source: Jarvis and Griffith, 2007; Jarvis 2008

Figure 2

Components of Cognitive Analytics

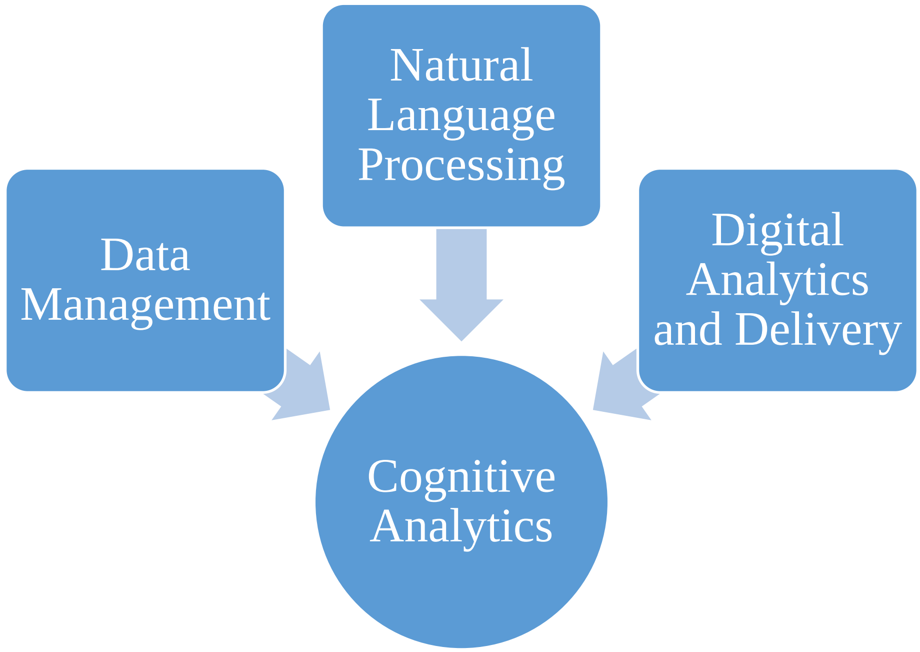


Figure 3

Observe-Orient-Decide-Act Decision Process

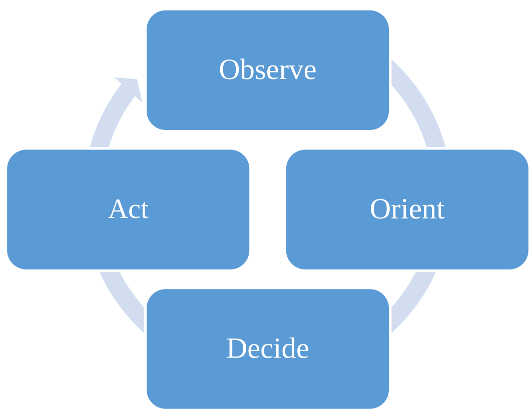


Figure 4

The Fifth Phase of the Political Risk Management Framework

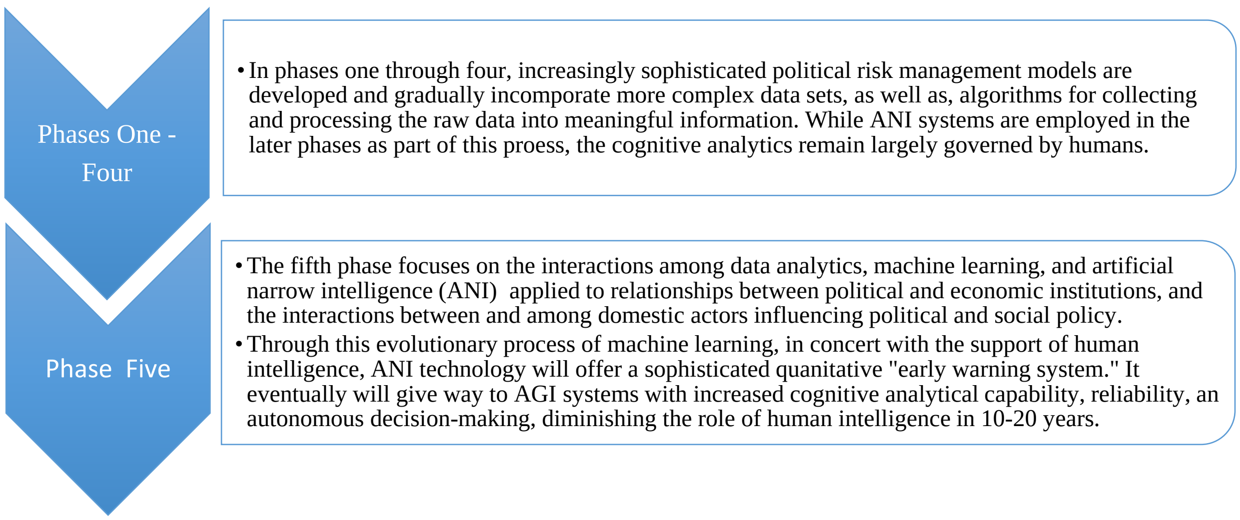
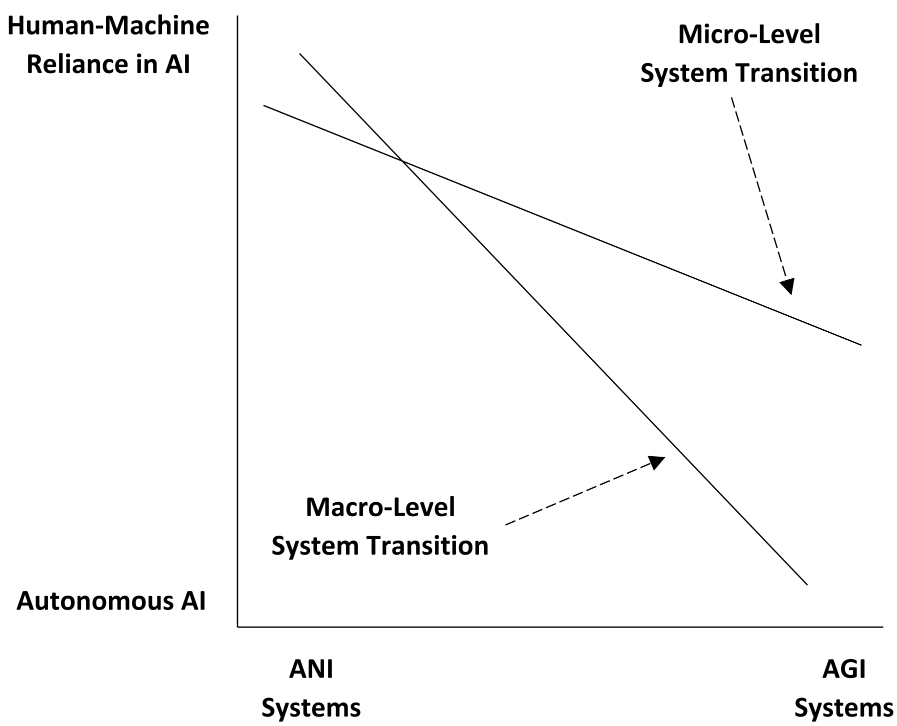


Figure 5

The Transition from Human-Machine Reliant ANI to Autonomous AGI in Political Risk Assessment: Macro and Micro-Level Systems Evolution Compared



Cover Letter

Dr. Mary Teagarden
Editor
Thunderbird International Business Review

Dear Dr. Teagarden:

Please accept the article ("Multinational Enterprises and Regulatory Expropriation: Artificial Intelligence and the Fifth Phase of Political Risk Management") for publication consideration in *Thunderbird International Business Review*.

The article has not been previously published and it is not currently under consideration elsewhere.

Yours truly,

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