MANAGING CORPORATIONS' RISK IN ADOPTING ARTIFICIAL INTELLIGENCE: A CORPORATE RESPONSIBILITY PARADIGM

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INTRODUCTION

Accelerating developments are being observed in machine learning (ML) technology as the capacities for data capture and ever-increasing computer processing power have significantly improved. This is a branch of artificial intelligence technology that is not 'deterministic,' but rather one that programs the machine to 'learn' from patterns and data[1] in order to arrive at outcomes, such as in predictive analytics.[2] It is observed that companies are increasingly exploring the adoption of various ML technologies in various aspects of their business models,[3] as successful adopters have seen marked revenue growth.[4]

ML raises issues of risk for corporate and commercial use that are distinct from the legal risks involved in deploying robots that may be more deterministic in nature.[5] Such issues of risk relate to *what* data is being input for the learning processes for ML, the risks of bias, and hidden, sub-optimal assumptions;[6] *how* such data is processed by ML to reach its 'outcome,' leading sometimes to perverse results such as unexpected errors,[7] harm,[8] difficult choices,[9] and even sub-optimal behavioural phenomena;[10] and *who* should be accountable for such risks.[11] While extant literature provides rich

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1 Gillian Hadfield, Center for Ethics and Law Biennial Lecture at University College London: Rules for Robots: Building Legal Infrastructure for Artificial Intelligence (June 18, 2019); Yanqing Duan, John S. Edwards & Yogesh K. Dwivedi, *Artificial Intelligence for Decision Making in the Era of Big Data – Evolution, Challenges and Research Agenda*, 48 INT'L J. INFO. MGMT. 63 (2019).

2 ERIC SIEGEL, PREDICTIVE ANALYTICS: THE POWER TO PREDICT WHO WILL CLICK, BUY, LIE, OR DIE (2013).

3 Arif Cam, Michael Chui & Bryce Hall, *Global AI Survey: AI Proves Its Worth, But Few Scale Impact*, MCKINSEY & CO. (Nov 22, 2019), https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact.

4 *Id*.

5 Curtis E.A. Karnow, *The Application of Traditional Tort Theory to Embodied Machine Intelligence*, *in* ROBOT LAW 51 (Ryan Calo, Michael Froomkin & Ian Kerr eds., 2019).

6 Kirsten Martin, *Ethical Implications and Accountability of Algorithms*, 160 J. BUS. ETHICS 835 (2019); Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54 (2019).

7 Contractual error in automated arrangements such as orders placed by Internet of Things machines. Samir Chopra & Laurence White, *Artificial Agents and the Contracting Problem: A Solution Via an Agency Analysis*, 2009 U. ILL. J.L. TECH. & POL'Y 363.

8 The fatal accident involving Elaine Herzberg with Uber's self-driving car. Richard Gonzales, *Fed Says Self-Driving Uber SUV Did Not Recognise Jaywalking Pedestrian in Fatal Crash*, NPR (Nov 7, 2019, 10:57 PM), https://www.npr.org/2019/11/07/777438412/feds-say-self-driving-uber-suv-did-not-recognize-jaywalking-pedestrian-in-fatal-?t=1591614086611.

9 Alfred R. Cowger, *Liability Considerations When Autonomous Vehicles Choose the Accident Victim*, 19 J. HIGH TECH. L. 1 (2018).

10 Tim Harford, *Expect Mischief as Algorithms Proliferate*, FIN. TIMES (Feb. 21, 2019), https://www.ft.com/content/3b9977a0-35c5-11e9-bb0c-42459962a812.

11 Discussions range from manufacturers' product liability, to users' vicarious liability, including

discussion of these issues, there are only emerging regulatory frameworks[12] and soft law in the form of ethical principles[13] to guide corporations navigating this area of innovation. This article intentionally focuses on corporations that deploy ML, rather than on producers of ML innovations, in order to chart a framework for guiding strategic corporate decisions in adopting ML. We argue that such a framework necessarily integrates corporations' legal risks and their broader accountability to society. The navigation of ML innovations is not carried out within a 'compliance landscape' for corporations, given that the laws and regulations governing corporations' use of ML are yet emerging. Corporations' deployment of ML is being scrutinised by the industry, stakeholders, and broader society as governance initiatives are being developed in a number of bottom-up quarters. We argue that corporations should frame their strategic deployment of ML innovations within a 'thick and broad' paradigm of corporate responsibility that is inextricably connected to business-society relations.

Section 1 defines the scope of ML that we are concerned about and distinguishes this from automated systems. We argue that the key risk that ML poses to corporations is unpredictability of results,[14] even if ML systems may perform efficiently and flawlessly most of the time.[15] Such unpredictability poses four categories of legal and non-legal risks for corporations, which we will unpack in Section 2: (a) risks of external harms and liability; (b) risks of regulatory liability; (c) reputational risks; and (d) risks of an operational nature and significant financial losses. These risks

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for employees, dangerous animals, children etc, to whether autonomous machines should bear their own liability. Eric Tjong Tjin Tai, *Liability for (Semi)Autonomous Systems: Robots and Algorithms*, *in* RESEARCH HANDBOOK IN DATA SCIENCE AND LAW ch. 4 (Vanessa Mak, Eric Tjong Tjin Tai & Anna Berlee eds., 2018); UGO PAGALLO, THE LAWS OF ROBOTS: CRIMES, CONTRACTS AND TORTS chs. 1, 2, 4–5 (2013); Gerhard Wagner, *Robot, Inc.: Personhood for Autonomous Systems?*, 88 FORDHAM L. REV. 591, 592 (2019); Paul Opitz, *Civil Liability and Autonomous Robotic Machines: Approaches in the EU and US* (Stanford Transatlantic Tech. L.F., Working Paper No. 43, 2019), https://www-cdn.law.stanford.edu/wp-content/uploads/2019/02/opitz_wp43.pdf; Andrew D. Selbst, *Negligence and AI's Human Users*, 100 B.U. L. REV. 1315 (2020); SAMIR CHOPRA & LAURENCE F. WHITE, A LEGAL THEORY FOR AUTONOMOUS ARTIFICIAL AGENTS (2011); Shawn Bayern, *The Implications of Modern Business Entity Law for the Regulation of Autonomous Systems*, 19 STAN. TECH. L. REV. 93 (2015).

12 Council Regulation 2016/679, 2016 O.J. (L 119) 1, 32 [hereinafter GDPR].

13 *See, e.g.*, *About Us*, P'SHIP ON AI, https://www.partnershiponai.org/about/#our-work (last visited June 7, 2021); *Asilomar AI Principles*, FUTURE OF LIFE INST., https://futureoflife.org/ai-principles/ (last visited June 7, 2021); AI4People's 7 AI Global Frameworks, AI4People (2020); *AI Ethics Framework*, WORLD ECON. FRAMEWORK, https://www.weforum.org/projects/ai-ethics-framework (last visited June 7, 2021).

14 Chris Curran & Anand Rao, *Briefing: Artificial Intelligence*, PWC (Jan. 22, 2018), http://usblogs.pwc.com/emerging-technology/briefing-ai/.

15 Efficiency is the predominant consideration of corporations. Ari Ezra Waldman, *Power, Process, and Automated Decision-Making*, 88 FORDHAM L. REV. 613 (2019).

do not insularly affect corporations and their shareholders, as both often interact with a broader narrative in relation to business-society relations. Indeed, these risks pose broader consequences for business-society relations.

Section 3 anchors the risks depicted above in the narratives of business-society relations by first examining their impact on the social, economic, and moral realms and, secondly, arguing that corporations should navigate these narratives in a 'thick and broad' paradigm of corporate responsibility.[16] This Section explains that the 'thick and broad' paradigm of corporate responsibility is based on the perspective that integrates corporations into citizenship within the broader social fabric. The location of corporate management of ML risks in this paradigm compels corporations to internalise this socially conscious perspective and to shape their strategic and risk management approaches to ML risks accordingly.

Section 4 explores the applicational implications for corporations in addressing ML risks within a thick and broad corporate responsibility paradigm. We argue that the deployment of ML provides corporations with both the opportunity and the social obligation to carry this out with social discourse and expectations in mind. ML technologies can potentially usher in major institutional change,[17] and corporate behaviour and leadership in adopting ML should be more holistically interrogated.[18] Section 5 concludes.

16 *See infra* Section 3.

17 JANNIS KALLINIKOS, THE CONSEQUENCES OF INFORMATION: INSTITUTIONAL IMPLICATIONS OF TECHNOLOGICAL CHANGE (2017).

18 WENDELL WALLACH, A DANGEROUS MASTER: HOW TO KEEP TECHNOLOGY FROM SLIPPING BEYOND OUR CONTROL (2015); Jacques Bughin & Eric Hazan, *Can Artificial Intelligence Help Society as Much as It Helps Business?*, MCKINSEY Q. (Aug. 6, 2019), https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/can-artificial-intelligence-help-society-as-much-as-it-helps-business.

I. CORPORATIONS' ADOPTION OF ML

Businesses increasingly deploy artificial intelligence (AI) systems in finance,[19] healthcare,[20] taxation,[21] sales and marketing,[22] production and manufacturing,[23] and risk management.[24] While there are different definitions for what constitutes "AI", at its core, AI are systems designed to reason and act like intelligent and rational human beings for the purpose of attaining specified objectives.[25] The deployment of AI has evolved from the business adoption of automation, which has been ongoing since the 1940s.[26] Automation is deterministic in that machines complete tasks in a self-governing manner 'by means of programmed commands combined with automatic feedback control to ensure proper execution of the instructions'.[27]

There is a relentless movement from 'automation' to 'autonomy' as machine development is steered towards ML. Machines would be elevated from slavishly performing pre-programmed commands to working out the most optimal and efficient routes to achieving performance. Such machines are programmed to process volumes of data within frameworks such as: 'natural language processing,'[28] which allows human language expressions to be directly engaged with instead of translation into code; 'decision trees'[29] that allow pathways to information analysis and processing to be organised

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19 ARTIFICIAL INTELLIGENCE IN FINANCIAL MARKETS: CUTTING-EDGE APPLICATIONS FOR RISK MANAGEMENT, PORTFOLIO OPTIMIZATION AND ECONOMICS (Christian L. Dunis, Peter W. Middleton, Andreas Karathanasopolous & Konstantinos Theofilatos eds., 2016).

20 HEALTHCARE AND ARTIFICIAL INTELLIGENCE (Bernard Nordlinger, Cedric Villani & Daniela Rus eds., 2020).

21 *How Tax Is Leveraging AI —Including Machine Learning —In 2019*, PwC (2019), https://www.pwc.com/cb/en/services/pdf/how-tax-leveraging-ai-machine-learning-2019.pdf.

22 Thomas Davenport, Abhijit Guha, Dhruv Grewal & Timna Bressgott, *How Artificial Intelligence Will Change the Future of Marketing*, 48 J. ACAD. MKTG. SCI. 24 (2020); PETER GENTSCH, AI IN MARKETING, SALES AND SERVICE (2019).

23 Ray Y. Zhong, Xun Xu, Eberhard Klotz & Stephen T. Newman, *Intelligent Manufacturing in the Context of Industry 4.0: A Review*, 3 ENG'G 616 (2017); Matthias Klumpp & Caroline Ruiner, *Regulation for Artificial Intelligence and Robotics in Transportation, Logistics, and Supply Chain Management: Background and Developments*, 20 NETWORK INDUS. Q. 3 (2018).

24 Saqib Aziz & Michael Dowling, *Machine Learning and AI for Risk Management*, *in* DISRUPTING FINANCE: FINTECH AND STRATEGY IN THE 21ST CENTURY (Theo Lynn, John G. Mooney, Pierangelo Rosati & Mark Cummins eds., 2019); *Artificial Intelligence Applied to Risk Management*, Fed'n Eur. Risk Mgmt. Ass'ns (2019).

25 *A Definition of AI: Main Capabilities and Scientific Disciplines*, Eur. Comm'n, High-Level Expert Grp. on Artificial Intel. (2019); MARGARET A. BODEN, AI: ITS NATURE AND FUTURE (2016).

26 Mikell P. Groover, *Automation*, BRITANNICA (Oct. 22, 2020), https://www.britannica.com/technology/automation.

27 *Id*.

28 Paulius Čerka, Jurgita Grigienė & Gintare Sirbikytė, *Liability for Damages Caused by Artificial Intelligence*, 31 COMPUT. L. & SEC. REV. 316 (2015).

29 LIOR ROKACH & ODED MAIMON, DATA MINING WITH DECISION TREES: THEORY AND APPLICATIONS (2d ed. 2008).

with statistical and consequential logic; or 'artificial neural networks,'[30] which simulate the human brain's associations and organise data in statistical but non-linear manners. ML processes data and recognises patterns within its learning frameworks in order to achieve certain outcomes and decisions. However, ML is still far from attaining 'super intelligence,'[31] the term used to describe AI able to replicate human intelligence. The development of AI is often discussed in three stages: narrow, general, and super.

Narrow AI refers to the ability of computers to undertake specific tasks, such as learning the rules of chess in order to play it.[32] The machine is trained with the rules of the game and voluminous data relating to previous plays and moves, in order to work out the pathways needed for it to play or compete.[33] ML is able to devise more than one manner of pattern recognition in order to achieve outcomes, surpassing the programmed robot that operates on a precise, pre-determined sets of rules.[34]

General AI is more ambitious, as it relates to machines with more 'holistic' or integrated capacity, simulating human reasoning that is more multi-faceted in nature.[35] Such a machine would not only be a chess player, Roomba vacuum, or facial recognition software, but more of an all-around android. Recent research given in conference proceedings shows that there has been only incremental development towards building general AI.[36] As

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30 *See, e.g.*, Mohammed Abbas Kadhim, M. Afshar Alam & Harleen Kaur, *A Multi-Intelligent Agent for Knowledge Discovery in Database (MIAKDD): Cooperative Approach with Domain Expert for Rules Extraction*, in INTELLIGENT COMPUTING METHODOLOGIES 602 (De-Shuang Huang, Kang-Hyun Jo & Ling Wang eds., 2014).

31 Michael Haenlein & Andreas Kaplan, *A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence*, 61 CAL. MGMT. REVS. 5 (2019).

32 L. Thorne McCarty, *Finding the Right Balance in Artificial Intelligence and Law*, *in* RESEARCH HANDBOOK ON THE LAW OF ARTIFICIAL INTELLIGENCE 55 (Woodrow Barfield & Ugo Pagallo eds., 2018).

33 Duan et al., *supra* note 1.

34 Hadfield, *supra* note 1; Arno R. Lodder, Visiting Fellow, Lecture at the London School of Economics and Political Science: Regulation of Algorithms (June 19, 2019).

35 Human reasoning is based on an integration of rationality, memory, contextual knowledge and behavioural shortcuts or heuristics, as well as communal factors like social conditioning, Philip N. Johnson-Laird, *Mental Models and Human Reasoning*, 107 PNAS 18243 (2010), different from the holistic and integrated nature of human reasoning, Lodder, *supra* note 34.

36 It is painfully challenging to teach AI to learn a new language. Alex Glushchenko, Andres Suarez, Anton Kolonin, Ben Goertzel, Claudia Castillo, Man Hin Leung & Oleg Baskov, *Unsupervised Language Learning in OpenCog*, *in* ARTIFICIAL GENERAL INTELLIGENCE 109 (Matthew Iklé, Arthur Franz, Rafal Rzepka & Ben Goertzel eds., 2018). However, there is more significant breakthrough in enabling AIs to design. Andreas Makoto Hein & Hélène Condat, *Can Machines Design? An Artificial General Intelligence Approach*, *in* ARTIFICIAL GENERAL INTELLIGENCE, *supra*, at 87.

the developments in communications robotics show,[37] general AI today remains rudimentary. An area of much-hyped development in general AI is that of self-driving cars,[38] as self-driving encompasses a number of different functions that, taken together, constitute the complex act of driving. General AI may attain greater human resemblance. However, in developing such general AI, a plethora of errors and hazards would have to be dealt with, such as the fatalities that have been caused by self-driving cars.[39]

Super AI refers to AI that is indistinguishable from human sentience and capacity. Fiction provides us with a glimpse of the heights super AI may one day attain, such as the fiercely independent AI character Ava in *Ex Machina*[40] or a more benign AI personality as in the Japanese animation *Time of Eve*.[41] Super AI and humans would live side by side and would be almost indistinguishable except for the laws of robotics that govern android behaviour, such as laws safeguarding the superiority of humans.[42] As fiction uncannily shows, developments towards super AI would necessarily be underpinned by policy choices involving law, governance, ethics, and social considerations such as inclusion and cohesion.

With scientific developments in the realm of narrow and possibly general AI, the corporate sector has been attracted to adopting the new capacities offered by such technology. This adoption has been incremental and focused on areas where there is strategic perception of a natural fit between ML and efficiency, revenue expansion, and cost reduction.[43] We provide a brief survey of corporate adoption of ML below.

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37 Kotaro Hayashi, Takayuki Kanda, Hiroshi Ishiguro, Tsukasa Ogasawara & Norihiro Hagita*, An Experimental Study of the Use of Multiple Humanoid Robots as a Social Communication Medium*, *in* UNIVERSAL ACCESS IN HUMAN-COMPUTER INTERACTION: APPLICATIONS AND SERVICES 32 (Constantine Stephanidis ed., 2011) (on AI mastering passive but not interactive conversation).

38 Google's subsidiary Waymo has launched a small self-driving taxi fleet in Phoenix, Arizona. Andrew Buncombe, *Waymo Launches First US Commercial Self-driving Taxi Service*, INDEPENDENT (Dec. 5, 2018, 10:50 PM), https://www.independent.co.uk/life-style/gadgets-and-tech/news/waymo-self-driving-taxi-service-google-alphabet-uber-robotaxi-launch-us-a8669466.html.

39 *Uber's Fatal Self-Driving Crash: All the News and Updates*, VERGE (Sept. 16, 2020), https://www.theverge.com/2018/3/28/17174636/uber-self-driving-crash-fatal-arizona-update; Charlotte Jee, *Tesla's Model 3 Autopilot Mode Was Activated Seconds Before a Fatal Crash*, MIT TECH. REV. (May 17, 2019), https://www.technologyreview.com/f/613549/teslas-model-3-autopilot-mode-was-activated-seconds-before-a-fatal-crash/.

40 EX MACHINA (A24 2014).

41 Eve no Jikan (Time of Eve) (2010). The laws of robotics are commonly derived from Issac Asimov. *Isaac Asimov's "Three Laws of Robotics"*, LIST OF LISTS, http://webhome.auburn.edu/~vestmon/robotics.html (last visited June 8, 2021).

42 For example, Asimov's three laws of robotics are referred to in Issac Asimov. *Isaac Asimov's "Three Laws of Robotics"*, *supra* note 41.

43 Karen Butner & Grace Ho, How the Human-Machine Interchange Will Transform Business Operations, 47 STRATEGY & LEADERSHIP 25 (2019).

First, corporations are attracted to ML's potential ability to manage increasing data volume and overload, including for compliance or risk management purposes. Human management of voluminous amounts of data can result in errors caused by fatigue or negligence, while ML may offer more consistent performance. The question, however, is whether the performance of ML is comparable to that of humans in respect to the decision-making or judgment phases of task performance related to the analysis and processing of data. ML is increasingly deployed in decision-making or judgment phases that are not necessarily straight-forward, repetitive, and low-level, but that may instead require case-by-case analysis and application.

For example, Deloitte provided a case study of an AI solution, developed for a client, that analysed the latter's employment tax obligations in order to enable more effective compliance.[44] The AI model developed by Deloitte was fed with Deloitte's own data such as a dictionary, tax laws and regulations, and various training data. Deloitte then worked with the client company to locate, extract, clean up, and analyse the company's data from its general ledger, payroll, and accounts payable systems. All the relevant data were then labelled according to different employment-related expenditure. The AI system was then trained with different sets of scenarios and questions to see if it could provide the correct answers for tax compliance.

However, autonomous data-management decision-making by ML entails risks of error and liability. There is a risk that sub-optimal outcomes can be attributed to the quality, representativeness, and completeness of data[45] or to the appropriateness of ML routes and pattern-recognition.[46] In relation to ML systems for bank risk management, commentators have opined that ML is helpful due to its ability to process complex and voluminous risk data.[47] However, risk data is often backward-looking and incomplete. They may capture 'known risks' and 'known unknowns' but

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44 Deloitte, Artificial Intelligence – Entering the World of Tax, at 5 (2019).

45 Thomas C. Redman, *If Your Data is Bad, Your Machine Learning Tools Are Useless*, HARV. BUS. REV. (Apr. 2, 2018), https://hbr.org/2018/04/if-your-data-is-bad-your-machine-learning-tools-are-useless; Eric J. Topol, *High-Performance Medicine: The Convergence of Human and Artificial Intelligence*, 25 NATURE MED. 44 (2019) (on how the inputting of synthetic sample data into IBM's Watson system, an AI system for assisting in oncological diagnosis, could contribute to erroneous performance).

46 Yavar Bathaee, The Artificial Intelligence Black Box and the Failure of Intent and Causation, 31 HARV. J.L. & TECH. 898 (2018).

47 Udo Milkau & Jürgen Bott, Active Management of Operational Risk in the Regimes of the "Unknown": What Can Machine Learning or Heuristics Deliver?, 6 RISKS 41 (2018).

often are unable to incorporate 'unknown unknowns.'[48] In relation to ML systems for financial institutions' implementation of anti-money laundering alert and reporting systems, the inherent lack of completeness of customer information and changing patterns of financial crime behaviour can severely challenge the essentially data-focused ML systems.[49] The efficiencies that may be offered by ML need to be balanced against the inherent risks in data-focused ML systems, entailing implications for legal and regulatory risks, to be discussed further in Section 2.

Next, corporations may be attracted to ML for its pattern-recognition capacities that are able to achieve end-to-end functions in a more efficient manner by cutting out intermediary steps or roles, possibly leading to better performance and cost-saving. One example of such deployment of ML systems is in global supply chain management, particularly in regard to the internet of things (IoT). In global supply chain management, ML is used to analyse demand and sales data to manage production, inventories, and stock availability.[50] Moreover, such data collection can itself be the subject of autonomous learning by the machine in an internet-of-things set-up. IBM describes this in a hypothetical scenario of supply chain management of car distribution networks. Data is collected automatically from car showrooms in relation to demand and customers' positive signals such as the amount of time spent lingering in certain areas in car showrooms. These inputs can be automatically processed and transmitted to relevant centers of operations and organisation in the supply chain to trigger production or inventory management.[51] In such deployment, ML systems may minimise errors committed by humans due to the complexity of data analytics required during intermediate steps. ML systems are even developed to manage risks of supply disruptions so that alternative avenues and channels can be efficiently pursued without delay.[52]

However, such supply chain management relies on the predictive analytics capabilities of ML, especially in relation to consumer demand levels. It remains uncertain whether such systems can be resilient against

48 *Id.*; *see also* THE KNOWN, THE UNKNOWN, AND THE UNKNOWABLE IN FINANCIAL RISK MANAGEMENT (Francis X. Diebold, Neil A. Doherty & Richard J. Herring eds., 2010).

49 Accenture Consulting, *Evolving AML Journey: Leveraging Machine Learning Within Anti-Money Laundering Transaction Monitoring*, (2017), https://www.accenture.com/_acnmedia/pdf-61/accenture-leveraging-machine-learning-anti-money-laundering-transaction-monitoring.pdf.

50 Karen Kim, *Artificial Intelligence in Supply Chain Management*, DISCO (July 19, 2019), https://www.project-disco.org/innovation/071919-artificial-intelligence-in-supply-chain-management/#.XTdKSW9KiCR.

51 Jen Clark, *What is the Internet of Things (IoT)?*, IBM (Nov. 17, 2016), https://www.ibm.com/blogs/internet-of-things/what-is-the-iot/.

52 Kim, *supra* note 50.

unexpected exogenous shocks to consumer sentiment, such as the Covid-19 crisis that began in 2020. Other risks, such as cybersecurity and hacking risks, may also need to be managed for ML systems that are connected across global networks.[53]

Another application of ML lies in achieving certain tasks without the need for intermediate steps (or human errors), for example, the increasing deployment of employee surveillance.[54] ML may be used to scan employee expense claims, communications, or emails in order to detect fraud or abuse. Although this may reduce operational risk and cost for companies, it also raises legal and ethical issues relating to employment and privacy.

The third common attraction of ML for corporate sector adoption lies in predictive analytics, which can help companies gain a competitive edge in achieving revenue and sales growth or minimise losses, such as in minimising productivity or default losses.[55] McKinsey[56] reports the most remarkable growth in corporate sector adoption of ML systems is for sales and marketing, as consumer behaviour data is harvested and fed into ML systems to predict consumer trends and demands. ML is used to proactively facilitate consumer purchase decisions, such as Amazon.com's 'what other items were bought by customers who bought your item.'[57] One example of a marketing ML system was developed by Intel. Prior to using ML, Intel relied on its sales and marketing analysts to conduct manual search of companies to identify potential sales leads. With the help of ML, Intel discovered new and better leads with greater accuracy at a faster pace.[58] Intel developed an in-house AI system to identify new markets and customers using ML, specifically supervised and semi-supervised learning and natural language processing models to create customer segmentation. Intel fed millions of pieces of textual data from the web into a neural network text classification model developed by a third party with a pre-trained multi-lingual language model developed by Google. The data

53 Cam et al., *supra* note 3.

54 Peter Buell Hirsch, *Tie Me to the Mast: Artificial Intelligence & Reputation Risk Management*, 39 J. BUS. STRATEGY 61 (2018).

55 ERIC SIEGEL, PREDICTIVE ANALYTICS: THE POWER TO PREDICT WHO WILL CLICK, BUY, LIE, OR DIE (2013).

56 Cam et al., *supra* note 3.

57 Bernard Marr, *Amazon: Using Big Data to Understand Customers*, BERNARD MARR & CO. (https://www.bernardmarr.com/default.asp?contentID=712 (last visited June 8, 2021).

58 Itay Lieder, Meirav Segal, Eran Avidan, Asaf Cohen & Tom Hope, *Learning a Faceted Customer Segmentation for Discovering New Business Opportunities at Intel*, *in* IEEE INTERNATIONAL CONFERENCE ON BIG DATA 6136 (Chaitanya Baru, Jun Huan, Latifur Khan, Xiaohua Hu, Ronay Ak, Yuanyuan Tian, Roger Barga, Carlo Zaniolo, Kisung Lee & Yanfang Fanny Ye eds., 2019).

include but are not limited to thousands of company sites appearing in Wikipedia. The data are labeled by Intel according to two categories, industries (retail, transportation, education, healthcare, communications, etc.) and roles (whether the companies are service providers, retailers, manufacturers, etc.). As for companies that are not labeled, Intel deploys semi-supervised learning which allows the system a free hand in determining the label, drawing from Intel's internal data, i.e. not from the web but from information that Intel already has by virtue of its existing business relationships with its clients.

Predictive analytics in sales and marketing using ML have helped not only Intel but many other surveyed companies to achieve superior revenue growth.[59] Further, predictive analytics is also used to help companies avoid losses, for example in human capital or productivity losses, or default losses for banks that can be caused by less than creditworthy borrowers.

Predictive analytics has been incrementally integrated into recruitment and hiring in order to detect talent and productivity characteristics, allowing companies to reduce productivity losses.[60] Such deployment of ML inevitably raises issues of ethics, discrimination, and privacy.[61] Predictive analytics is also used extensively in credit decisions, especially by fintech companies using algorithmic credit scoring and decision-making processes.[62] The resulting extensive issues in profiling, discrimination, financial inclusion/exclusion, ethics, and privacy are discussed at length by commentators.[63]

In the above examples of popular use of ML by the corporate sector, various risks abound, and there is an essential risk/return tradeoff for strategic consideration by corporations.[64] Increased efficiency, minimization of errors, and revenue growth are attractive, but companies turning to ML systems run ML-inherent risks and accompanying risks that

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59 Eric T. Bradlow, Manish Gangwar, Praveen Kopalle & Sudhir Voleti, *The Role of Big Data and Predictive Analytics in Retailing*, 93 J. RETAILING 79 (2017).

60 JAC FITZ-ENZ & JOHN R. MADDOX II, PREDICTIVE ANALYTICS FOR HUMAN RESOURCES (2014).

61 WALLACH, *supra* note 18.

62 James Maguire*, 12 Examples of Artificial Intelligence: AI Powers Business*, DATAMATION (Sept. 13, 2019); Mirka Snyder Caron, *The Transformative Effect of AI on the Banking Industry*, 34 BANKING & FIN. L. REV. 169 (2018).

63 Katja Langenbucher, *Responsible A.I.-Based Credit Scoring – A Legal Framework*, 31 EUR. BUS. L. REV. 527 (2020); Nikita Aggarwal, *The Norms of Algorithmic Credit Scoring*, 80 CAMBRIDGE L.J. 42 (2021).

64 Andrea Bonime-Blanc, *Technology, Trust and Ethics: An Actionable Governance Toolkit for a Disruptive Time*, CARRIER MGMT. (Oct. 11, 2018), https://www.carriermanagement.com/features/2018/10/11/185226.htm.

are legal, regulatory and reputational in nature.[65] Section 2 explores the landscape of risks for corporations considering or presently adopting ML and argues ultimately that, besides targeted regulatory[66] and external ethical approaches,[67] an internally-robust 'corporate responsibility' framework is crucial for corporations to manage the risks of adopting ML systems.

II. MAPPING THE LANDSCAPE OF RISKS FOR CORPORATIONS ADOPTING ML SYSTEMS

Corporations have been pioneers in adopting technological innovations in production, service, operations, distribution, and delivery,[68] battling legal risks along the way.[69] Non-human innovative installations gave rise to legal issues decades ago as courts set new boundaries of rights and obligations, for example, the 1970s case regarding the introduction of unmanned automated parking facilities in *Thornton v. Shoe Lane Parking Ltd*.[70] The adoption of ML systems by corporations would also give rise to legal issues in relation to rights and obligations that need to be clarified and possibly even regulated.[71]

This section maps out the terrain of emerging legal and related non-legal risks that corporations need to manage. The McKinsey survey on adoption of ML systems by the corporate sector shows that corporations often focus excessively on the opportunities offered by ML systems but fail to engage sufficiently with managing the risks of adopting ML systems.[72] As the strategic adoption of ML systems is a global phenomenon for many

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65 Hirsch, *supra* note 54; *infra* Section 2.

66 The General Data Protection Regulation addresses some aspects of algorithmic profiling and data subjects' right of challenge. GDPR, *supra* note 12, art. 22; *see also* Lilian Edwards & Michael Veale, *Slave to the Algorithm? Why a 'Right to an Explanation' Is Probably Not the Remedy You Are Looking For*, 16 DUKE L. & TECH. REV. 18 (2017). Regulatory approaches are suggested in Ravi B. Parikh, Ziad Obermeyer & Amol S. Navathe, *Regulation of Predictive Analytics in Medicine*, 363 SCIENCE 810 (2019).

67 The development of ethical standards by the EU, Asilomar Conference, OECD and AI4People group, see *infra* Section 2.

68 HISTORY OF ENTREPRENEURSHIP: INNOVATION AND RISK-TAKING, 1200–2000 (Mark Casson & Catherine Casson eds., 2013); William Lazonick, *The Innovative Firm*, *in* THE OXFORD HANDBOOK OF INNOVATION 29 (Jan Fagerberg, David C. Mowery & Richard R. Nelson eds., 2005); Alice Lam, *Organizational Innovation*, *in* THE OXFORD HANDBOOK OF INNOVATION, *supra*, at 115.

69 *See, e.g.*, Richard A. Epstein, *Legal Liability for Medical Innovation*, 8 CARDOZO L. REV. 1139 (1987).

70 Thornton v. Shoe Lane Parking Ltd. [1971] QB 163 (Eng.) (on whose responsibility it is to draw the consumer's attention to onerous terms in an unmanned automated parking facility).

71 Michael Callier & Harly Callier, *Blame It on the Machine: A Socio-Legal Analysis of Liability in an AI World*, 14 WASH. J.L. TECH. & ARTS 49 (2018).

72 Cam et al., *supra* note 3.

companies, especially those that are well-resourced and transnational in nature, we attempt to provide a compass or framework for managing the risks of strategic ML adoption at a high level, one that 'sits above' any particular legal or regulatory regime. In this manner, we are cognisant of differences in legal and regulatory fragmentation faced by transnational companies whose ML adoption and deployment may be global but nevertheless argue that an overarching framework that guides and is not mired in jurisdiction-based detail would benefit corporations.

Leaving technical risks aside, we identify four sets of legal and related non-legal risks arising from corporate adoption of ML systems, namely: (a) legal risks dealing largely with private liability; (b) regulatory risks dealing with compliance obligations or infringement of existing regulatory standards, perhaps in an unexpected manner; (c) reputational risks dealing with relations with stakeholders or communities in possibly disoriented or frayed relations; and (d) operational and financial losses, dealing with the losses occasioned to corporations where unexpected ML performance occurs, which may also be connected with the liability and risk issues in (a), (b), and (c). We argue that it is crucial for corporations adopting ML systems to concurrently manage these four sets of risks.

A. Legal Risks

This part addresses the legal risks faced by corporations adopting ML systems in relation to private liability and contains a dedicated section reserved for discussion of regulatory risks. There are at least two types of private liability relating to ML systems: commercial and third-party. Regarding the former, corporations deploying ML may face contractual liability risks if the performance of ML affects their contractual performance. It is possible that corporations mindful of the novelties in adopting ML systems would seek to manage contractual liability risks in a 'blanket' manner by way of contractual exclusions of liability. In a business-to-business context, exclusions may be upheld as reasonable.[73] However, this may be more unpredictable if a consumer is involved.[74] In terms of

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73 Unfair Contract Terms Act (U.K.) 1977 c. 2–3; U.C.C. § 2-316 (AM. L. INST.); Tod M. Turley, *Expert Software Systems: The Legal Implications*, 8 COMPUT. L.J. 455, 457 (1988); Maruerite E. Gerstner, *Liability Issues with Artificial Intelligence Software*, 33 SANTA CLARA L. REV. 239, 254, 262 (1993) (citing Roland B. Desilets, Jr., Note, *Software Vendors' Exposure to Products Liability for Computer Viruses*, 9 COMPUT. L.J. 509, 524 (1989)).

74 Consumers are protected under the Consumer Rights Act (U.K.) 2015 c. 15, which subject the use of exclusion clauses against them to stringent control. However, it is opined that consumer law does not certainly protect consumers seamlessly in an ML context. *See* Przemysław Pałka, Agnieszka Jabłonowska, Hans-W. Micklitz & Giovanni Sartor, *Before Machines Consume the Consumers* (Eur.

third-party liability, corporations deploying ML systems may incur private liability if harm, such as physical injury, is caused to third parties, for example when a self-driving car hits a pedestrian.[75] Private liability may also be incurred if economic losses are suffered by third parties, where relationships of proximity[76] warrant a duty of care to be imposed on the corporation. Third-party liability risks may be more unpredictable and unmanageable than contractual liability risks, and the difficulty in managing these risks is exacerbated by the challenges ML systems pose to existing liability frameworks, such as in the US and UK, in the following ways:

(i) there is uncertainty as to whether the corporate deployer of ML systems *should* be subject to liability if decisions made by ML systems have been devised within the 'black box' of ML learning routes ('the normative implications for innovation');

(ii) there is uncertainty as to how the applicable legal framework for negligence can be transposed into the ML context ('the positive applications of existing law');

(iii) there is uncertainty as to how contributory negligence operates in terms of the expected norms of conduct on the part of the third party interacting with the ML system; and

(iv) there is general uncertainty in terms of judicial leanings and development, cost of litigation and any compensatory liability.

On the normative implications for innovation, there is extensive debate as to whether deployers of ML systems should be made liable for third-party harms, as ML systems are designed to arrive at their own decisions. Should the AI instead be regarded as personally liable,[77] the consequence being that

Univ. Inst. Dep't of Law, Working Paper No. 12, 2018).

75 *See, e.g.*, Sean Hollister, *Uber Won't Be Charged with Fatal Self-Driving*, VERGE (Mar. 5, 2019, 7:55 PM), https://www.theverge.com/2019/3/5/18252423/uber-wont-be-charged-with-fatal-self-driving-crash-says-prosecutor (describing Uber's self-driving car accident that killed a pedestrian in Arizona). However, for a contrary opinion in the EU (focusing on UK and Germany), see Michael P. Chatzipanagiotis & George Leloudas, *Automated Vehicles and Third-Party Liability: A European Perspective*, 2020 U. ILL. J.L. TECH. & POL'Y 109.

76 Caparo Indus. PLC v. Dickman [1990] UKHL 2 (Eng.). The scope for third-party economic loss recovery in the US is however negligible. *See* Ralph C. Anzivino, *The Economic Loss Doctrine: Distinguishing Economic Loss from Non-Economic Loss*, 91 MARQ. L. REV. 1081 (2008).

77 Shawn Bayern, Thomas Burri, Thomas D. Grant, Daniel M. Häusermann, Florian Möslein & Richard Williams, *Company Law and Autonomous Systems: A Blueprint for Lawyers, Entrepreneurs, and Regulators*, 9 HASTINGS SCI. & TECH. L.J. 135 (2017); Iria Giuffrida, *Liability for AI Decision-Making: Some Legal and Ethical Considerations*, 88 FORDHAM L. REV. 439, 440 (2019).

normative jurisprudence should move away from fault and responsibility[78] on the part of the deployer of ML systems? In this manner, we would focus only on restoring or compensating the victim, moving away from doctrinal analyses of human 'fault' or 'responsibility'.[79] Commentators have suggested that third-party harms resulting from the deployment of ML systems could be compensated by a pre-funded institution[80] that pays for the social cost of innovation or by insurance arrangements.[81] Such normative ideas have traction, especially if we consider the possible mainstreaming of self-driving cars in the future. It would likely be a more efficient system if social provision on the whole can be made for ML risks leading to third party harms to facilitate innovation.[82] Innovative companies would then not run the risk of being excessively penalised, and it would likely be impracticable and costly to expect complex litigation to be borne by drivers and third-party individuals contesting the boundaries of existing private law.

However, it may be argued that we would be too quick to assume that norms of 'fault,' responsibilities, and conduct cannot be satisfactorily fashioned,[83] and both ethical and legal interrogation[84] must take place as innovation becomes socially accepted. This argument is more 'coherentist' in nature as, according to Brownsword,[85] a dominant legal response to new technology is often that of 'seeking coherentism' with existing legal frameworks, assuming that existing legal frameworks have technology-neutral and timeless qualities to interrogate a new development. In this manner, the legal interpretation and categorisation of a novel feature can be made coherent with existing law. According to this approach, the legal risks for corporations deploying ML systems may chiefly be in the realm of positive applications of law rather than normative legal reforms.

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78 Peter M. Asaro, *The Liability Problem for Autonomous Artificial Agents* (Ass'n for the Advancement of Artificial Intel., Conference Paper, 2016).

79 This is opposed in F. Patrick Hubbard, *Sophisticated Robots: Balancing Liability, Regulation, and Innovation*, 66 FLA. L. REV. 1803 (2014).

80 Andrea Bertolini, *Insurance and Risk Management for Robotic Devices: Identifying the Problems*, 16 GLOB. JURIST 291 (2016); Giuffrida, *supra* note 77; Eur. Comm'n, Expert Grp. on Liab. & New Techs., *Liability for Artificial Intelligence and Other Emerging Technologies*, (2019).

81 Woodrow Barfield, *Liability for Autonomous and Artificially Intelligent Robots*, 9 J. BEHAV. ROBOTICS 193 (2018); David C. Vladeck, *Machines Without Principals: Liability Rules and Artificial Intelligence*, 89 WASH. L. REV. 117 (2014).

82 Bryan H. Choi, *Crashworthy Code*, 94 WASH. L. REV. 39 (2019).

83 Deborah G. Johnson, *Technology with No Human Responsibility?*, 127 J. BUS. ETHICS 707 (2015); Arthur Kuflik, Computers in Control: Rational Transfer of Authority or Irresponsible Abdication of Autonomy?, 1 ETHICS & INFO. TECH. 173 (1999).

84 Hin-Yan Liu, *Irresponsibilities, Inequalities and Injustice for Autonomous Vehicles*, 19 ETHICS INFO. & TECH. 193 (2017).

85 ROGER BROWNSWORD, LAW, TECHNOLOGY AND SOCIETY: RE-IMAGINING THE REGULATORY ENVIRONMENT 154 (2019).

However, it is generally acknowledged that ML systems present novel features not well-accommodated in positive applications of existing law. If ML systems make autonomous decisions, how does this change the scope of corporate deployers' duty and standard of care to third parties? [86] The deployment of ML able to make autonomous determinations means that human agency would be 'one-step removed.' In this manner, would duties for human agents pertain to general frameworks for operations and safety management, rather than the precise operation of the ML system? In a self-driving car, if the role of humans is reduced to that of monitoring the driving environment and to regain control only when requested by the car or in exceptional situations, then the duty of care would attach to monitoring functions and not the driving function as such.

Further, as positive applications of third-party liability laws require the finding of a causal connection between the victim and the 'fault' or responsibility that can be attached to a legal person, it is worth considering what difficulties the autonomous nature of ML decision-making would pose for such positive application of law.[87] Bathaee,[88] for instance, argues that causation needs to be reformed in order to more holistically capture the frameworks of human agency in relation to ML operations, so that proximity for causation can be extended.[89] For example, for highly autonomous ML systems human agency in design or higher-level frameworks of operation should be regarded as causally proximate. Casey[90] argues that traditional causation concepts can still work, provided that we have total transparency of ML systems' black boxes and decision-making processes, so that attribution of fault or responsibility can be made.

However, under both approaches, it can be argued that 'fault' or 'responsibility' would be attributed to designers or supervisors of ML systems.' It is perhaps no surprise that, under a coherentist approach, to properly interrogate how positive applications of law would apply to harms caused by ML systems, product liability of the ML system is of prime importance and has led to extensive commentary.[91] Relying on product

86 Karnow, *supra* note 5; Selbst, *supra* note 11.

87 Bertolini, *supra* note 80; Liu, *supra* note 84; Barfield, *supra* note 81; Liability for Artificial Intelligence and Other Emerging Technologies, *supra* note 80.

88 Bathaee, *supra* note 46.

89 Opitz, *supra* note 11.

90 Bryan Casey, *Robot Ipsa Loquitur*, 108 GEO. L.J. 225 (2019).

91 Wagner, *supra* note 11, at 592; Barfield, *supra* note 81; Vladeck, *supra* note 81. Product liability is supported for specific systems such as medical robots. *See* Vincent M. Brannigan & Ruth E. Dayhoff, *Liability for Personal Injuries Caused by Defective Medical Computer Programs*, 7 AM. J.L. & MED.

liability as the doctrinal destination for attribution of compensatory liability[92] may become a norm, but this is undesirable because product liability is yet another body of law that needs to be interrogated in order for ML systems to fit in.[93] Further, such a distribution of legal risk can be an impediment to innovative companies, especially small or medium sized enterprises.[94]

The extent to which third parties may be contributorily negligent is also likely to be subject to doctrinal contestation as new expectations of conduct in relation to third-party engagement with ML must be fashioned. Pedestrian jaywalkers can be regarded as contributorily negligent even when drivers are expected to brake and slow down, too, ahead of the accident. However, are pedestrian jaywalkers contributorily negligent if an approaching self-driving car misclassifies the pedestrian wrongly and accelerates or fails to slow down in advance of the accident?[95]

The interrogation of ML risks within private law precepts relating to commercial and third-party liability brings about many uncertainties in terms of doctrinal fits and normative implications for law or regulatory reform. Indeed, the lack of clarity in how law would be applied or interpreted is not merely a 'legal' question but also imports of socio-legal aspects in terms of how social responses to legal uncertainties would drive positive or normative legal responses.

In the social realm, the legal risks of third-party liability arising from corporate deployment of ML systems such as Uber's self-driving cars and IBM's Watson do not only affect the physical or economic interests of claimants in actual or potential lawsuits. Rather, these legal risks raise broader issues about the companies' responsibilities to society in ensuring that their development and deployment of ML systems does not create social externalities but instead creates social benefits that exceed social harm.[96] As such, we cannot stop at merely analysing whether and how private law should be reformed to minimise and deter such social harms.

123 (1981).

92 The UK class action against Tesla was settled. *See* Tina Bellon, *Tesla Agrees to Settle Class Action over Autopilot Billed as 'Safer'*, REUTERS (Feb. 7, 2018), https://uk.reuters.com/article/uk-tesla-autopilot-lawsuit/tesla-agrees-to-settle-class-action-over-autopilot-billed-as-safer-idUKKCN1IQ1SR.

93 Barfield, *supra* note 81; Vladeck, *supra* note 81.

94 Choi, *supra* note 82.

95 Alexis C. Madrigal, *Uber's Self-Driving Car Didn't Malfunction, It Was Just Bad*, ATLANTIC (May 24, 2018), https://www.theatlantic.com/technology/archive/2018/05/ubers-self-driving-car-didnt-malfunction-it-was-just-bad/561185/.

96 Contissa et al., *Towards consumer-empowering artificial intelligence*, Proc. of the Twenty-Seventh In'l Joint Conf. on Artificial Intel. 5150 (2018).

The 'social licence to operate' can affect how positive and normative legal conceptions should be shaped, and corporations must be responsive to this.[97] Companies can become 'bound' to extra-legal practices driven by the need to achieve social legitimacy. For example, corporations in the extractive industry work intensely with stakeholder inputs as their business operations integrally affect communities' environments and livelihoods, and stakeholder inputs and well-being are crucial to the sustenance of business models in those communities.[98]

In considering private law risks to companies in deploying ML systems, one can be focused only upon rectifying and restoring the bilateral relationships between the claimant and defendant,[99] or implications for legal certainty and how they shape future corporate behaviour. This narrow approach needs to be avoided in relation to corporate deployment of ML risks, not only because the positive and normative developments of private law are dynamic, but also because dynamism is driven by underpinning socio-legal narratives about the fairness, social acceptability and legitimacy of ML deployment by corporations.

B. Regulatory Risks

The deployment of ML systems by corporations entails regulatory risks in three ways. First is the question of fit between existing regulatory standards and the operational or functional implications of ML systems. Second, regulatory compliance issues are arising especially in relation to data collection, management and retention by corporations. Third, there would potentially be new regulatory regimes or standards to contend with in relation to the use of ML systems, especially if they become more widely adopted.

The adoption of ML systems may affect how corporations meet their regulatory standards and requirements,[100] standards which can differ

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97 Peter G. Leonard, *Social Licence and Digital Trust in Data-Driven Applications and AI: A Problem Statement and Possible Solutions* (2018) (manuscript), https://ssrn.com/abstract=3261228.

98 Kieren Moffat, Justine Lacey, Airong Zhang & Sina Leipold, *The Social Licence to Operate: A Critical Review*, 89 FORESTRY 477 (2016); Melanie (Lain) Dare, Jackie Schirmer & Frank Vanclay, *Community Engagement and Social Licence to Operate*, 32 IMPACT ASSESSMENT & PROJECT APPRAISAL 188 (2014).

99 ERNEST J. WEINRIB, THE IDEA OF PRIVATE LAW (1995); Jacob Eisler, *The Limits and Promise of Instrumental Legal Analysis*, 47 J.L. & SOC'Y 499 (2020); *cf.* RICHARD A. POSNER, THE ECONOMICS OF JUSTICE (1981).

100 *See, e.g.*, Senthil Selvaraj, *The Skinny on How Narrow AI Will Affect Banks*, RMA J., Mar. 6, 2019, at 42.

between jurisdictions. Where ML systems are intended to facilitate more efficient compliance,[101] corporations face inherent risk in ML systems not meeting regulatory standards if there is failure to embed correctly regulatory interpretation and expectations. For example, this is particularly important in anti-money laundering compliance in the financial sector or the use of robo-advisors to provide investment recommendations for financial customers.[102] In the context of robo-advice, where the processing of investor information and the matching with investment products is 'algorithmised,' the conduct of business regulation applicable to investment advice remains the same.[103] Technically speaking, most 'robo-advisers' are more deterministic than ML in nature, but there are emerging developments for ML in investment advice. The standards of expected conduct, whether in collecting investor information or ascertaining suitability of recommendations,[104] or in customer due diligence and raising of alerts to comply with anti-financial crime[105] obligations, remain qualitatively the same, regardless of technological deployment. Hence, where new technology is used, firms need to embed regulatory compliance in technological application, even if the mix between human agency and technological processing is different from company to company.

However, as regulation is not machine-readable,[106] the automation of regulatory compliance is based on assumptions in relation to regulatory interpretation and supervisory expectations. Legal risk can arise for corporations and their ML system suppliers in relation to the making of such assumptions. Further, it is unclear whether regulatory compliance obligations can be perfectly transposed onto the modalities of software.[107] On the other hand, automating compliance also raises behavioural issues for

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101 Andrea Falcione, *Taking Corporate Compliance Programs Digital*, NAT'L DEF. (Sept. 3, 2019), https://www.nationaldefensemagazine.org/articles/2019/9/3/ethics-corner-taking-corporate-compliance-programs-digital.

102 Such as robo-advice. Tom Baker & Benedict G.C. Dellaert, *Regulating Robo Advice Across the Financial Services Industry*, 103 IOWA L. REV. 713 (2018); Facundo Abraham, Sergio L. Schmukler & José Tessada, *Robo-Advisors: Investing through Machines* (World Bank Research and Policy Briefs, No. 134881, 2019).

103 Iris H.-Y. Chiu, *Transforming the Financial Advice Market – The Roles of Robo-Advice, Financial Regulation and Public Governance in the UK*, 35 BANKING & FIN. L. REV. 9 (2019).

104 *See, e.g.*, Directive 2014/65/EU of the European Parliament and of the Council of 15 May 2014 on Markets in Financial Instruments, 2014 O.J. (L 173/349), art. 25; FIN. CONDUCT AUTH., CONDUCT OF BUSINESS SOURCEBOOK 9, 9A (2021).

105 *See, e.g.*, Directive (EU) 2015/849 of the European Parliament and of the Council of 20 May 2015 on the Prevention of the Use of the Financial System for the Purposes of Money Laundering or Terrorist Financing, 2015 O.J. (141/73), ch. II.

106 Ralf Huber, *Making Regulation Machine Readable*, *in* THE REGTECH BOOK (Janos Barberis, Douglas W. Arner & Ross P. Buckley eds., 2019).

107 James Grimmelmann, *Regulation by Software*, 114 YALE L.J. 1719 (2005).

firms that fail to culturally embed the spirit of compliance. Firms need to beware of a form of behavioural 'auto-pilot' where their staff become overly reliant on ML systems and fail to adhere to the spirit of the regulation.[108]

Next, the risks of data collection and management by corporations that deploy ML systems have been widely canvassed.[109] Corporations face regulatory risks in relation to data collection and protection and data subjects' rights, such as the 'right to be forgotten' under the EU General Data Protection Regulation (GDPR). Questions have been raised, including whether the right to be forgotten applies to data fed into ML systems and how this would affect the matrix of information and learning routes implemented by ML systems.[110] Where companies utilise data subjects' information in ML systems that would result in decisions affecting them, such as algorithmic credit scoring, challenges can arise if ML systems are found to be systemically biased or discriminatory.[111] These risks would likely require an enterprise-wide approach on the part of corporations to address them, including data compliance, risk management, technologically-expert staff, and a joined-up governance framework.

Finally, corporations are likely to face regulatory risk in terms of changing and new regulatory standards and regimes, especially if ML systems become more widely adopted.[112] There is the possibility of overarching regimes or standards, such as those found in the GDPR, as well as sectoral standards such as in automotive, healthcare, or financial sectors.[113] However, this is an emerging development, and corporations must be prepared for any policy changes that may be introduced. The European Commission in particular requires corporations that may be thinking of deploying ML with an increased risk of harm to adopt precautionary measures.[114] In this spirit, corporations cannot merely wait for

108 Kenneth A. Bamberger, Technolo*gies of Compliance: Risk and Regulation in a Digital Age*, 88 TEX. L. REV. 669 (2009).

109 Jim Shook, Robyn Smith & Alex Antonio, *Transparency and Fairness in Machine Learning Applications*, 4 TEX. A&M J. PROP. L. 443 (2018); Margot E. Kaminski, *The Right to Explanation, Explained*, 34 BERKELEY TECH. L.J. 189 (2019); Shlomit Yanisky-Ravid & Sean K. Hallisey, *"Equality and Privacy by Design": A New Model of Artificial Intelligence Data Transparency via Auditing, Certification, and Safe Harbor Regimes*, 46 FORDHAM URB. L.J. 428 (2019).

110 Yuan Yuan, *Machine Unlearning: Fighting for the Right to Be Forgotten*, SYNCED (May 2, 2020), https://syncedreview.com/2020/02/05/machine-unlearning-fighting-for-the-right-to-be-forgotten/.

111 *Supra* note 63.

112 Callier & Callier, *supra* note 71; *Liability for Artificial Intelligence and Other Emerging Technologies*, *supra* note 80.

113 Tjong, *supra* note 11.

114 *Liability for Artificial Intelligence and Other Emerging Technologies*, *supra* note 80.

or rely on regulatory parameters to shape the boundaries of their behaviour but should instead engage proactively with the public interests that policy-makers desire to protect. Corporations should thus prepare to consider notions of 'harm' broadly in relation not only to bilateral physical or economic harms, but also more broadly social, economic and moral harms. In this manner, decisions to adopt or deploy ML systems should not merely be considered in a technologically deterministic[115] or efficiency-focused manner but should incorporate corporations' consideration about their share of responsibility in bringing about and managing change for themselves and the society impacted by them.

Corporations are also likely to be involved with regulators, stakeholders, industry, and others in the shaping of future regulatory regimes.[116] The capacity to engage in policy discourse is one that corporations should invest in, likely best developed in an enterprise-wide manner that involves personnel from strategic, operational, innovation, risk management, and compliance departments.

C. Reputational Risks

Reputational risks for corporations deploying ML systems can arise in two ways, but they affect the corporation's business-society relations more generally. One is that corporations' legal or regulatory risks entail reputational risks. The second is that corporations' use of ML systems within the 'grey areas' or 'gaps' in private or regulatory law is perceived with caution, as such use entails changes and disorientation to society's expectations of or relations with the corporation.

A leading, notorious example in the UK is the Cambridge Analytica scandal, where Facebook failed to monitor the illegal harvesting of data by Cambridge Analytica's ML systems in order to build up profiles of Facebook users for targeted political advertising.[117] Cambridge Analytica has since been dissolved and social trust in Facebook has lessened

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115 Horst Eidenmüller, *Machine Performance and Human Failure: How Shall We Regulate Autonomous Machines?*, 15 U. MD. J. BUS. & TECH. L. 109 (2019); Jack M. Balkin, *The Three Laws of Robotics in the Age of Big Data*, 78 OHIO STATE L.J. 1217 (2017).

116 A general trend towards 'co-regulation' is proposed in Michèle Finck, *Digital Co-Regulation: Designing a Supranational Legal Framework for the Platform Economy*, 43 EUR. L. REV. 47 (2018).

117 Nicholas Confessore, Cambridge Analytica and Facebook: The Scandal and the Fallout So Far, N.Y. TIMES (Apr. 4, 2018), https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html; Elizabeth Gibney, *The Scant Science Behind Cambridge Analytica's Controversial Marketing Techniques*, NATURE (Mar. 29, 2018), https://www.nature.com/articles/d41586-018-03880-4.

significantly.[118] This has also entailed a broader movement in the US and UK to consider imposing regulatory control over 'big tech' firms such as Facebook, Amazon, and Google.[119]

Where companies' use of ML gives rise to risks of exploitation and misuse of data, breach of privacy, and discrimination, such as in the use of facial recognition software[120] and algorithmic credit scoring[121], the reputation of companies will be adversely affected.[122] However, these episodes, besides raising regulatory risks, also entail the broader issue of the role of companies in promoting or undermining human rights, social values, and fundamental principles.[123] Are corporations deploying ML systems insularly for their own benefit without any consideration of how such deployment promote the long-term trust between business and society? For example, Chun discusses commercial deployment of facial recognition technologies as essentially an issue of business-society relations. Personal data is effectively entrusted to corporate or commercial entities and this entails a paradigm of social trust. How then should facial recognition technologies be used so as to embed respect for such social entrustment even if the deployment of these technologies is pursuant to private/commercial purposes?[124] Where companies deploying ML become intimately involved with their customers, suppliers, stakeholders, etc. through possession and

118 Herb Weisbaum, *Trust in Facebook Has Dropped by 66 Percent Since the Cambridge Analytica Scandal*, NBC NEWS (Apr. 18, 2018, 2:08 PM), https://www.nbcnews.com/business/consumer/trust-facebook-has-dropped-51-percent-cambridge-analytica-scandal-n867011.

119 Madhumita Murgia & Kate Beioley, *UK to Create Regulator to Police Big Tech Companies*, FIN. TIMES (Dec. 18, 2019), https://www.ft.com/content/67c2129a-2199-11ea-92da-f0c92e957a96; Sintia Radu, *The World Wants More Tech Regulation*, U.S. NEWS (Jan 15, 2020, 12:01 AM), https://www.usnews.com/news/best-countries/articles/2020-01-15/the-world-wants-big-tech-companies-to-be-regulated.

120 Sarah Chun, Facial Recognition Technology: A Call for the Creation of a Framework Combining Government Regulation and a Commitment to Corporate Responsibility, 21 N.C. J.L. & TECH. 99 (2020).

121 Langenbucher, *supra* note 63; Aggarwal, *supra* note 63.

122 Baobao Zhang, *Public Opinion Lessons for AI Regulation*, BROOKINGS (Dec. 10, 2019), https://www.brookings.edu/research/public-opinion-lessons-for-ai-regulation/; Mark Latonero, *Governing Artificial Intelligence: Upholding Human Rights & Dignity*, Data & Soc'y (2018), https://apo.org.au/sites/default/files/resource-files/2018-10/apo-nid196716.pdf.

123 Emilie C. Schwarz, Human vs. Machine: A Framework of Responsibilities and Duties of Transnational Corporations for Respecting Human Rights in the Use of Artificial Intelligence, (2019) 58 COLUM. J. TRANSNAT'L L. 232 (2019).

124 Chun, *supra* note 120, argues that companies use facial recognition technology pursuant to their commercial purposes but companies may not be aware of the wider context of data subjects' rights, such as under human rights law, and the need to protect data subjects from misuse or abuse of their facial profiles. This area should be governed by corporate engagement with ethics and social responsibility, and companies should develop explicit and transparent policies to be accountable to society.

processing of their data,[125] such data entrustment entails interdependence and vulnerability in the same manner as businesses that are operating in an integrated manner in their communities. Social legitimacy and expectations are an integral part of corporations' considerations in deploying ML systems.

The deployment of ML in sales and marketing also entails risks of consumption manipulation[126] (but there is also evidence of ML systems being used to forestall mis-selling led by humans).[127] Further, corporate reputation may also be undermined where ML systems disrupt work patterns and the political economy, a key aspect of business-society relations.[128] Corporate deployment of ML systems cannot be insularly decided upon as wider effects would at the very least boomerang upon corporations in the form of reputational risks. Siebecker likens the deployment of ML by corporations to the use of the private property of corporations' capital in a manner that affects society and hence such powers must be exercised in a manner consistent with Berle and Means' articulation of 'trust,' which includes social trust.[129]

Corporations should be cognisant of their share of contribution to social disruptions, upheaval, or disorientation in adopting and deploying ML systems in a manner that affects their relationship with the public and society. Indeed, corporations should consider their role in beneficence[130] and how its vision of human progress should be balanced against sacrifices that may occur along the way. Such sacrifices can relate to replaced jobs or job security in industries where ML may take over tasks[131] and the trade-off

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125 Natania Locke & Helen Bird, *Perspectives on the Current and Imagined Role of Artificial Intelligence and Technology in Corporate Governance Practice and Regulation*, 35 AUSTRALIAN J. CORP. L. 4 (2020).

126 See Palka et al., *supra* note 96, on how consumers may be unduly influenced and develop technology dependencies.

127 Lee Kyung-min, *Banks Employ AI to Forestall Mis-Selling*, KOREA TIMES (Feb. 16, 2020, 4:19 PM), https://www.koreatimes.co.kr/www/biz/2020/02/126_283373.html.

128 Mona Sloane, *Making Artificial Intelligence Socially Just: Why the Current Focus on Ethics Is Not Enough*, LSE BPP (July 6, 2018), https://blogs.lse.ac.uk/politicsandpolicy/artificial-intelligence-and-society-ethics/.

129 Michael R. Siebecker, *Making Corporations More Humane Through Artificial Intelligence*, 45 J. CORP. L. 95 (2020).

130 The first of the ethical principles proposed by the AI4People group, see Luciano Floridi, Josh Cowls, Monica Beltrametti, Raja Chatila, Patrice Chazerand, Virginia Dignum, Christoph Luetge, Robert Madelin, Ugo Pagallo, Francesca Rossi, Burkhard Schafer, Peggy Valcke & Effy Vayena, *AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations*, 28 MINDS & MACHS. 689 (2018).

131 Chris Fleissner, *Inclusive Capitalism Based on Binary Economics and Positive International Human Rights in the Age of Artificial Intelligence*, 17 WASH U. GLOB. STUD. L. REV. 201 (2018); Kathleen Wilburn & Ralph Wilburn, Challenges for Managing Business with 21st Century Technology,

between efficiency and autonomy, such as in the Internet of Things industry.[132]

D. Operational and Financial Losses

Although ML systems have much to offer corporations in terms of performance enhancement, efficiency, and risk management, corporations may suffer operational and financial losses when ML systems perform unexpectedly in their 'normal' course of operations. Arguably, the case involving Tyndaris Investments in the UK is one such example.[133] Tyndaris uses ML technologies for algorithmic management of trading decisions. Such management is based on ML analysis of trading and market data. Tyndaris attracted Hong Kong billionaire Samathur Li to let it manage, through investment company VWM, almost US$2.5 billion in the AI-powered hedge fund. However, on one calamitous day, Tyndaris purportedly lost US$20 million. VWM instructed Tyndaris to stop trading. Tyndaris then brought a claim against VWM for unpaid investment management fees of US$3 million. VWM counterclaimed against Tyndaris for misrepresentation, among other claims. Unexpected performance by ML systems can lead to customer grievances and claims, private law liability, and loss in revenue such as the unpaid fees claimed by Tyndaris. If ML systems like Tyndaris's are used in proprietary trading by financial institutions, trading and investment losses may be incurred by the corporate user on its own account. Further, if regulatory liability is implicated such as data breaches, firms can suffer further losses from fines and penalties. The GDPR for example provides for the possibility for firms to be fined up to 2% or 4% of their worldwide revenue depending on the severity of breach.[134]

For corporate users of ML systems designed and supplied by another, accountability for their operational losses may also lie with the sellers/suppliers of the ML software. Whether and to what extent corporate users are able to recoup their losses for malfunction or substandard ML systems depends on whether they can successfully sue the sellers/suppliers, primarily on the basis of product liability, which, as mentioned above, raises

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9 REV. BUS. & FIN. STUD. 13 (2018).

132 Tom Allen & Robin Widdison, *Can Computers Make Contracts*, 9 HARV. J.L. & TECH. 25 (1996); CHOPRA & WHITE, *supra* note 11, at ch. 4.

133 Jessica Messier, *Investor Sues Company Over Artificial Intelligence Advice*, MY TECH DECISIONS (May 28, 2019), https://mytechdecisions.com/compliance/investor-sues-company-over-artificial-intelligence-advice/.

134 Ben Wolford, *What Are the GDPR Fines*?, GDPR.EU, https://gdpr.eu/fines/ (last visited June 9, 2021).

uncertainties in terms of doctrinal application. For example, in the UK it is unclear whether corporate users' procurement of ML systems amounts to a contract of sale under the Sale of Goods Act 1979 (SGA) or a supply of service under the Supply of Goods and Services Act 1982 (SGSA), as ML systems may come in hardware housing or as downloadable software, affecting their characterisation as goods or services.[135] The application of the SGA or SGSA leads to different legal consequences in terms of sellers'/suppliers' liabilities and responsibilities and to what extent corporate users can call them to account. If the SGA applies, the seller is strictly liable in terms of description, fitness for purpose and satisfactory quality. If the SGSA applies, the supplier is only liable if it has breached the duty to exercise reasonable care and skill. Establishing the negligence of suppliers of ML systems is likely challenging, as ML systems do not come in a 'ready and complete' set that the corporate procurer simply deploys for its purpose. Rather, the corporate procurer may play a role in designing and testing the ML systems, which raises implications for the issues of satisfactory quality under the SGA as well as contributory negligence under the SGSA.[136] Further, exclusions of liability may also be effective between the corporate procurer and the supplier of ML systems, thereby rendering it more difficult for the corporate procurer to recoup its losses.

Although operational and financial losses present real risks to corporations deploying ML systems, such risks are not merely confined to corporations and their potential relationships in private law liability. In some instances, the corporate deployment of ML systems can cause wider ripple effects, such as systemic risks to financial markets. For example, 'flash crashes'[137] in stock markets caused by glitches in algorithmic trading software employed by particular traders can potentially be of systemic consequence. Such wider implications should be internalised by corporations in deploying ML systems so as to be cognisant of the potential social footprint of their ML operations.

Corporations' deployment of ML systems involves uncertainties in relation to the four sets of key risks that should be managed in parallel. In mapping out the nature of the four sets of risks above, we observe that these risks are dynamic, uncertain in scope and extent, and can also be characterised as 'transnational' and 'socio-legal' in nature. Addressing legal and regulatory risks may instinctively be thought of as being tied to specific

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135 Lim & Chiu, *supra* note 93.
136 *Id.*
137 Joshua Warner, *Flash Crashes Explained*, IG (May 3, 2019, 8:39 AM), https://www.ig.com/sg/trading-strategies/flash-crashes-explained-190503.

jurisdictions, but where legal approaches or regulatory policies are emerging and fragmented globally, corporations are not only addressing compliance needs demanded by any particular jurisdiction but require a higher-level framework to cope with the dynamic and shifting nature of legal and regulatory risks. Further, the reputational and operational risks, and even the legal and regulatory risks, resulting from ML deployment are engaged with stakeholder relationships, social scrutiny, and emerging policy reform, situating such risk management within a broader fabric that is not corporate-centric or narrowly-framed within legal and regulatory precepts.

This article proposes that, in this dynamic context, corporations can best cope by adopting a holistic and high-level framework for governing and managing ML risks, anchored in a widely-defined paradigm of corporate responsibility that incorporates high levels of strategic governance, corporate governance framework and business-society relations.

III. FRAMING CORPORATIONS' ML RISKS WITHIN THE CORPORATE RESPONSIBILITY PARADIGM

This Section argues that the 'Corporate Responsibility' (CR) paradigm should form the overarching framework for corporations' risk management of ML risks. This is because the CR paradigm is able to accommodate the transnational and socio-legal character of corporations' unique risk management needs in ML deployment.

Carroll's pyramid of corporate social responsibility has often been the starting point for explaining the holistic nature of a corporation's 'responsibility paradigm.'[138] Corporations may be primarily responsible for economic production and wealth generation, but they are also nested within a paradigm of external expectations in relation to citizenship,[139] including philanthropy. Corporations may be steered by frameworks of law and regulation that provide boundaries for behaviour, but they are also situated within a fabric of social expectations and community values and norms beyond what is legalised.[140]

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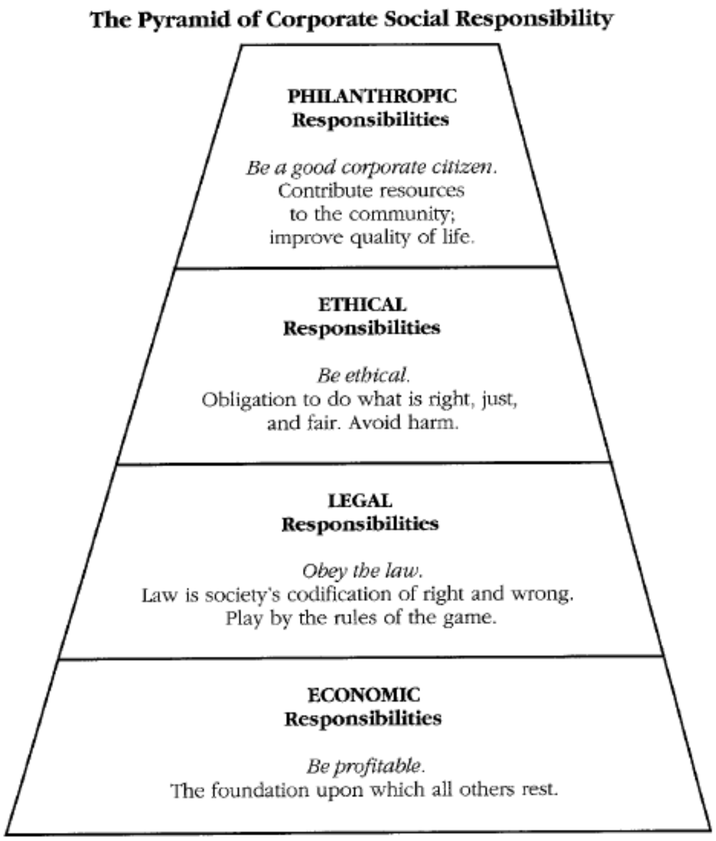
138 Archie B. Carroll, *The Pyramid of Corporate Social Responsibility: Toward the Moral Management of Organizational Stakeholders*, 34 BUS. HORIZONS 39 (1991).

139 Hazel Henderson, *Transnational Corporations and Global Citizenship*, 43 AM. BEHAV. SCIENTIST 1231 (2000); ANDREW CRANE, DIRK MATTEN & JEREMY MOON, CORPORATIONS AND CITIZENSHIP ch. 1 (2008).

140 John Douglas Bishop, *For-Profit Corporations in a Just Society: A Social Contract Argument*



Source: Archie B Carroll, 'The Pyramid of Corporate Social Responsibility: Toward the Moral Management of Organisational Stakeholders' Business Horizons 39 (1991).

The nature of ML risks for corporations can be characterised across the pyramidal spectrum, and the CR paradigm appropriately caters for corporations' holistic management of ML risks. Further, the CR paradigm is appropriate for corporations as an overarching framework to manage ML risks because such a paradigm accommodates inter-disciplinary perspectives and is not overly susceptible to the quantitative insularity of traditional risk management[141] nor the perverse incentives surrounding an

Concerning the Rights and Responsibilities of Corporations, 18 BUS. ETHICS Q. 191 (2008); THOMAS DONALDSON, CORPORATIONS & MORALITY ch. 3 (1982).

141 See René Stultz, *Risk Management Failures: What Are They and When Do They Happen?*, 20 J. APPLIED CORP. FIN. 39 (2008), specifically on such application of risk management in the financial sector. *See also* DOUGLAS HUBBARD, THE FAILURE OF RISK MANAGEMENT: WHY IT'S BROKEN AND HOW DO WE FIX IT? chs. 8–9 (2009).

instrumental approach to legal compliance.[142] The CR paradigm is able to respond to the emerging governance initiatives for AI/ML, many of which are situated in the realm of 'ethics,' an interdisciplinary combination of norms, values, socio-legal, policy, and governance perspectives.[143]

There are increasing calls to corporations deploying ML systems to adhere to ethical principles.[144] The slowness of legal and regulatory policy to articulate particular standards of conduct reflects complex discourse in this area,[145] and ethical principles have arisen to fill the gap. However, the fragmentation of these bodies of ethical principles also poses a challenge to corporations in selecting what to adhere to and in relation to how that selection may be perceived by stakeholders and society. There has been a proliferation of ethical principles from various international bodies, think tanks, and voluntary groups. In this respect, should corporations consider issuing their own ethical codes?[146] Should relevant sectors develop industry codes, such as the IEEE's Code?[147] Or are principles and codes issued by stakeholder or other expert groups, such as the Asilomar Principles[148] and the AI4People Principles, more credible as representing the terms that societies have negotiated with businesses?[149]

The above analysis advances our argument that corporate management of ML risks should be framed in broad and holistic terms, integrating business-society relations. We propose that corporations should manage ML risks in a thick and broad conception of corporate responsibility, in order to avoid applying a form of corporate responsibility that is seen

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142 Christine E. Parker, Robert Eli Rosen & Vibeke Lehmann Nielsen, *The Two Faces of Lawyers: Professional Ethics and Business Compliance with Regulation*, 22 GEO. J. LEGAL ETHICS 201 (2009).

143 Corporate responsibility is often conceptualised as an outward-facing paradigm to stakeholders and society, and this is often related to capabilising companies in relation to business ethics. *See* Kenneth E. Goodpaster, *The Concept of Corporate Responsibility*, 2 J. BUS. ETHICS 1 (1983); Jerry D. Goodstein & Andrew C. Wicks, *Corporate and Stakeholder Responsibility: Making Business Ethics a Two-Way Conversation*, 17 BUS. ETHICS Q. 375 (2007).

144 Julia Bossmann, *Top 9 Ethical Issues in Artificial Intelligence*, WORLD ECON. F. (Oct. 21, 2016), https://www.weforum.org/agenda/2016/10/top-10-ethical-issues-in-artificial-intelligence/.

145 *See, e.g., Liability for Artificial Intelligence and Other Emerging Technologies, supra* note 80.

146 *See, e.g.*, *Artificial Intelligence at Google: Our Principles*, GOOGLE AI, https://ai.google/principles/ (last visited June 9, 2021); Trips Reddy, *The Code of Ethics for AI and Chatbots that Every Brand Should Follow*, IBM (Oct. 15, 2017), https://www.ibm.com/blogs/watson/2017/10/the-code-of-ethics-for-ai-and-chatbots-that-every-brand-should-follow/.

147 *The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems*, IEEE SA, https://standards.ieee.org/industry-connections/ec/autonomous-systems.html (last visited June 9, 2021).

148 *Asilomar AI Principles*, *supra* note 13.

149 Floridi et al., *supra* note 130.

primarily to cater for public relations.[150] We also locate such corporate responsibility as a form of governance in the 'decentred' theory of regulation and explain it as a paradigm that is distinguished from narrow or insular conceptions of calculative risk management or public relations-washing.

A. Thick and Broad Conception of Corporate Responsibility

First, we argue that corporations should uphold a thick and broad conception of corporate responsibility as the paradigm for navigating ML risks. This is drawn from Sjåfell and Bruner's[151] 'thick' conception of sustainability, explained as integrating the 'social foundation' upon which corporations operate, and not merely having a peripheralised notion of external consciousness. Focused on sustainability, Sjåfell and Bruner argue that corporations are not insular entities but are operating within a context in relation to the planetary boundaries of the earth's environmental and eco-systems[152] and in relation to public goods such as the UN Sustainable Development Goals.[153] As such, corporate behaviour cannot blithely exist in a clear-cut public-private divide or be oblivious to the wider context of expectations with regard to appropriate behaviour and positive acts of citizenship.

We apply this notion more broadly to corporate responsibility: in the context of ML deployment that can pervasively and significantly impact the social, economic, and moral realms of community and society. As illustrated above, such deployment cannot merely be regarded as fulfilling efficiency needs on the part of corporations.[154] A thick and broad notion of corporate responsibility disavows narrow or cosmetic displays of corporate responsibility which are usually justified by the business case alone,[155] or

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150 See *infra* section titled 'Thick and Broad Conception of Corporate Responsibility.'

151 Beate Sjåfell & Christopher M. Bruner, *Corporations and Sustainability*, *in* THE CAMBRIDGE HANDBOOK OF CORPORATE LAW, CORPORATE GOVERNANCE AND SUSTAINABILITY 3 (Beate Sjåfell & Christopher M. Bruner eds., 2019).

152 The nine planetary boundaries explained by the Stockholm Resilience Center. *The Nine Planetary Boundaries*, STOCKHOLM RESILIENCE CTR., https://www.stockholmresilience.org/research/planetary-boundaries/planetary-boundaries/about-the-research/the-nine-planetary-boundaries.html (last visited June 9, 2021).

153 The seventeen sustainable development goals, see *The 17 Goals*, UNITED NATIONS, https://sustainabledevelopment.un.org/?menu=1300 (last visited June 9, 2021).

154 Waldman, *supra* note 15.

155 Steve Tombs, *The Functions and Dysfunctions of Corporate Social Responsibility*, *in* THE CORPORATION: A CRITICAL, MULTI-DISCIPLINARY HANDBOOK 346 (Grietje Baars ed., 2017); Paul K. Shum & Sharon L. Yam, *Ethics and Law: Guiding the Invisible Hand to Correct Corporate Social Responsibility Externalities*, 98 J. BUS. ETHICS 549 (2011); James A.H.S. Hine & Lutz Preuss, *"Society Is out There, Organisation Is in Here": On the Perceptions of Corporate Social Responsibility Held by*

regarded as simply a voluntary management tool,[156] stakeholder-relations exercise[157] or charitable activity. Such a notion demands that business strategy, governance, and key aspects of corporate operations be interrogated within a responsibility framework,[158] so that 'responsible' actions or activities are not siloed or peripheral.[159] The practical implications of this will be fleshed out in Section 4, involving corporate governance, enterprise-wide frameworks for risk management and responsible innovation, as well as substantive and procedural approaches.

The thick and broad paradigm of corporate responsibility is based on corporate power[160] and leadership[161] to transform socio-economic relations, exchanges, and modalities in general.[162] Waldman[163] argues that the deployment of ML is generally a reflection of corporate power based on corporations' resources and leadership in innovation. A thick and broad corporate responsibility paradigm for navigating ML risks would compel corporations to subject the exercise of private power to socially-conscious evaluations.[164]

Further, corporate use of ML is poised to bring about not only significant benefit but also great risk to social fabric, cohesion, and trust.[165] The use of ML transforms work relations and human-machine interfaces,[166] resulting in new risks in relation to displacement, work configuration and mental and social well-being.[167] ML transforms business processes such as

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Different Managerial Groups, 88 J. BUS. ETHICS 381 (2009).

156 Michael S. Aßländer, Corporate Social Responsibility as Subsidiary Co-Responsibility: A Macroeconomic Perspective, 99 J. BUS. ETHICS 115 (2011); Ronen Shamir, Socially Responsible Private Regulation: World-Culture or World-Capitalism?, 45 L. & SOC'Y REV. 313 (2011).

157 Krista Bondy, Jeremy Moon & Dirk Matten*, An Institution of Corporate Social Responsibility (CSR) in Multi-National Corporations (MNCs): Form and Implications*, 111 J. BUS. ETHICS 281 (2012). *But see* Ulf Henning Richter, Drivers of Change: A Multiple-Case Study on the Process of Institutionalization of Corporate Responsibility Among Three Multinational Companies, 102 J. BUS. ETHICS 261 (2011).

158 Bonime-Blanc, *supra* note 64.

159 Vanessa M. Strike, Jijun Gao & Pratima Bansal, *Being Good While Being Bad: Social Responsibility and the International Diversification of US Firms*, 37 J. INT'L BUS. STUD. 850 (2006).

160 J.E. PARKINSON, CORPORATE POWER AND RESPONSIBILITY (1995).

161 *See, e.g.*, Julia M. Puaschunder, *Intergenerational Leadership: An Extension of Contemporary Corporate Social Responsibility Models*, 2 CORP. GOVERNANCE & ORGANIZATIONAL BEHAV. 7 (2018).

162 See *infra* Section 4.

163 Waldman, *supra* note 15.

164 Kristijan Krkač, *Corporate Social Irresponsibility: Humans vs Artificial Intelligence*, 15 SOC. RESP. J. 786 (2019).

165 Floridi et al., *supra* note 130; Leonard, *supra* note 97.

166 Such as in production and manufacturing, entailing physical, labour, and human rights risks.

167 Dimple Agarwal, Josh Bersin, Gaurav Lahiri, Jeff Schwartz & Erica Volini, *AI, Robotics, and Automation: Put Humans in the Loop*, DELOITTE (Mar. 28, 2018),

internal and external due diligence, the configuration of expert tasks and external accountability.[168] Corporations should place themselves firmly within the social fabric[169] as a starting point in considering deployment of ML, in terms of their citizenly and 'neighbourly' relations with stakeholders and society. Indeed, Hickman and Petrin argue that the European Commission's Ethics Guidelines for Trustworthy AI—under which AI systems should be developed and used in "[a] sustainable, environmentally friendly [manner], considering broader society and other sentient beings"—potentially require corporations to use AI systems in a manner that is focused not only on themselves but on the wider social context. The Guidelines arguably present a paradigmatic challenge to the traditional shareholder-centric focus of corporate theory and practice.[170]

We also argue that the thick and broad notion of corporate responsibility is consonant with corporations' roles in the decentred landscape for governance of ML. Black[171] argues that certain areas are fraught with conditions that make them challenging for public sector regulators to assume complete control over their governance. Decentred regulation is appropriate in the face of five preconditions, namely complexity, fragmentation, interdependencies, ungovernability, and the rejection of a clear private-public distinction. Indeed, the final aspect is a consequence of the first four. 'Complexity' refers to the nature of problems that may need to be dealt with. 'Fragmentation' refers to the fragmentation of knowledge, resources and capacity for control in the regulatory space. 'Interdependencies' refers to the dynamics between the participants in the regulatory space, co-producing and co-enforcing norms of governance. 'Ungovernability' refers to the autonomy and unpredictability of actor behaviour in the regulatory space.

The landscape of ML technologies arguably presents all four conditions listed above. ML technologies tend towards decision-making and execution of actions that are relatively autonomous and opaque, and ML development

https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2018/ai-robotics-intelligent-machines.html.

168 Such as the use of ML in risk management that deals with internal and external accountability, see Jeanne Boillet, *Why AI Is Both a Risk and a Way to Manage Risk*, EY (Apr. 1, 2018), https://www.ey.com/en_gl/assurance/why-ai-is-both-a-risk-and-a-way-to-manage-risk.

169 Siebecker, *supra* note 129; Bughin & Hazan, *supra* note 18.

170 Eleanore Hickman & Martin Petrin, *Trustworthy AI and Corporate Governance – The EU's Ethics Guidelines for Trustworthy Artificial Intelligence from a Company Law Perspective* (2020) (manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3607225.

171 Black, *Decentring Regulation: Understanding The Role Of Regulation And Self-Regulation In A 'Post- Regulatory' World*, 54 CURRENT LEGAL PROBS. 103 (2001).

and governance, for example in relation to their control and explicability[172] are influenced by different stakeholders such as regulators, users, industry, experts and other stakeholders to different degrees. Governance of ML technologies is not technologically determined but determined by discourse between scientists, ethicists, policy-makers, industry, users, and stakeholders.[173] The inherently inter-disciplinary and interdependent needs in developing ML entail a fragmented and de-centred landscape where concerned actors bring to bear different capacities and perspectives. In such a decentred landscape, it would be facile to maintain a simple public-private distinction amongst governance participants. All parties involved are engaged with private benefits and costs in relation to ML development and deployment, as well as the public goods and risks that revolve around ML.

Regulatory instruments in this landscape are still emerging. For example, the EU's General Data Protection Regulation provides for aspects of corporations' internal governance and risk management in relation to data,[174] as well as redress mechanisms for affected data subjects.[175] Many issues remain outstanding as Section 2 has discussed, issues which remain unresolved in law or regulation. It also remains open whether specialist agencies should be set up as ML regulators.[176] The European Commission has, in view of such uncertainties, set out a high level framework for principles of legal liability and duties, such as a strict liability principle for use of AI that increases risk of harm; a duty for ML developers to provide logging functions in order for evidence to be adduced when unpredictable risks occur and access to justice and evidence by complainants.[177] It remains to be seen how and whether some of these may be incorporated into the European product liability regime and how European member states may incorporate these into their private law regimes. In this emerging landscape where hard law initiatives remain slow and tentative,[178] the ethical principles

172 One of the six principles developed by the AI4People group, Floridi et al., *supra* note 130. *See also* Andrew D. Selbst & Julia Powles, *Meaningful Information and the Right to Explanation*, 7 INT'L DATA PRIV. L. 233 (2017).

173 Bughin & Hazan, *supra* note 18; Floridi et al., *supra* note 130 (on the importance of inter-disciplinary development of AI governance).

174 See GDPR, *supra* note 12, arts. 35–39, on the institution of data impact assessment evaluations by companies and the role of the data protection officer. *See also* Lilian Edwards & Michael Veale, *Slave to the Algorithm? Why a 'Right to an Explanation' Is Probably Not the Remedy You Are Looking For*, 16 DUKE L. & TECH. REV. 18 (2017).

175 See GDPR, *supra* note 12, ch. 3, art. 22, which provides for a right to challenge automated data profiling. *See also* Shook et al., *supra* note 109; Kaminski, *supra* note 109.

176 Yanisky-Ravid & Hallisey, *supra* note 109.

177 *Liability for Artificial Intelligence and Other Emerging Technologies*, *supra* note 80.

178 Ryan Hagemann, Jennifer Huddleston Skees & Adam Thierer, *Soft Law for Hard Problems:*

discussed above have tentatively filled the gap.[179] However there are a number of these bodies of principles and their influence is only now emerging.

We turn to discuss how a thick and broad paradigm of corporate responsibility would provide the framework for corporations' navigation of the legal and related non-legal risks associated with ML. Such a framework should integrate corporations' private interests and the public aspects of their power and citizenship, so that the use of ML is integrally located within business-society relations.

IV. THE APPLICATION OF THE CORPORATE RESPONSIBILITY PARADIGM TO MANAGING ML RISKS

In a thick and broad corporate responsibility paradigm, companies that deploy ML should ensure that strategic decisions are taken at the highest corporate governance levels and that operational decisions and review are made in an enterprise-wide manner. These two aspects prevent insularity on the part of the corporation and tend towards broader perspectives.

A. Corporate Governance

First, we suggest that senior management and corporate boards should be concerned about the risks we depict in Section 2. In a narrow manner, these risks may sometimes be regarded as 'risk management' matters that merely affect the financial bottom-lines and viability of companies.[180] However, more broadly, such 'risk management' matters are often not only matters of financial consequence but also matters of culture[181] which reflect a company's disposition, values and structures in decision-making. Culture matters for success and long-term viability,[182] and, at a broader level,

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The Governance of Emerging Technologies in an Uncertain Future, 17 COLO. TECH. L.J. 37 (2018).

179 *See supra* notes 111–14.

180 Christoph Van der Elst & Marijn van Daelen, *Risk Management in European and American Corporate Law* (Eur. Corp. Gov. Inst., Working Paper No. 122, 2009), http://ssrn.com/abstract=1399647.

181 Risk management as reflecting corporate cultures discussed in Anette Mikes, *Risk Management and Calculative Cultures* (2007) (manuscript), http://ssrn.Com/Abstract=1138636, and ANNETTA CORTEZ, WINNING AT RISK: STRATEGIES TO GO BEYOND BASEL (2011), on a holistic definition of risk culture incorporating corporate organisational culture.

182 Organisational culture may be regarded as a ubiquitous 'glue' of shared perceptions in a firm or assumptions and beliefs underlying organisational work practices in the firm or units in the firm. *See* EDGAR H. SCHEIN, ORGANIZATIONAL CULTURE AND LEADERSHIP (2010); JOANNE MARTIN, ORGANIZATIONAL CULTURES: MAPPING THE TERRAIN (2001). Culture, corporate strategy, and success are discussed in Boris Groysberg, Jeremiah Lee, Jesse Price & J. Yo-Jud Cheng, *The Leader's Guide to Corporate Culture*, HARV. BUS. REV. (Jan./Feb. 2018), https://hbr.org/2018/01/the-culture-factor.

successful companies often treat risk management as an enterprise-wide phenomenon,[183] integrating different departments of personnel and at many levels in order to achieve higher perspectives and cohesion in action.

Commentators propose that governance oversight at the corporate board level is crucial for ML deployment. Suggestions include clarifying directors' duties for responsible deployment of ML,[184] and the implications from the European Commission's Guidelines for AI.[185] Further, commentators propose that companies institute corporate board committees to oversee the deployment of innovative technologies,[186] and the appointment of Chief Innovation Officers[187] whose remit is not merely to develop technology, such as the role of Chief Technology Officers in many companies,[188] but to oversee the development and deployment of new technologies in a responsible manner, working with relevant compliance, ethics and responsibility departments.[189]

Hickman and Petrin,[190] however, question the assumption underlying the above corporate governance proposals, i.e. change in human leadership is expected at the highest governance levels in companies. Such an assumption may not be well-placed, as there are trends towards appointing ML to have voting power on corporate boards[191] if not to assist them with information analysis.[192] If corporate governance structures change towards integrating ML, then the assumption that human leadership on Boards can provide the relevant corporate governance oversight for the corporation's

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183 Brian W. Nocco and René M. Stultz, *Enterprise Risk Management: Theory and Practice*, 18 J. APPLIED CORP. FIN. 8 (2006); CORTEZ, *supra* note 181.

184 Siebecker, *supra* note 129; Kieran Moynihan, *What Will the Board of the Future Look like?*, ACCOUNTANCY IR. (Dec. 3, 2018), https://www.charteredaccountants.ie/Accountancy-Ireland/Articles2/ethics-and-governance/Latest-News/what-will-the-board-of-the-future-look-like.

185 Hickman & Petrin, *supra* note 170.

186 Roger M. Barker & Iris H.-Y. Chiu*, From Value Protection to Value Creation: Rethinking Corporate Governance for Promoting Firm Innovation*, 23 FORDHAM J. CORP. & FIN. L. 437 (2018).

187 Timo Matthias Spitzer, *The Importance of Human Leadership with Integrity in a Highly Regulated and Tech-Relevant Corporate Environment*, 10 HARV. BUS. L. REV. 1 (2020).

188 Nick Ismail, *The 4 Different Types of CTO – Which One Are You?*, (Sept. 12, 2017), https://www.information-age.com/4-different-types-cto-123468506/. The profiles are highly business-oriented and there is a gap meeting the responsibility dimension.

189 Bonime-Blanc, *supra* note 64.

190 Hickman & Petrin, *supra* note 170.

191 Rob Wile, *A Venture Capital Firm Just Named an Algorithm to its Board of Directors—Here's What It Actually Does*, BUS. INSIDER (May 14, 2014, 1:19 AM), https://www.businessinsider.com.au/vital-named-to-board-2014-5.

192 Gary L. Evans, *Disruptive Technology and the Board: The Tip of the Iceberg*, 3 ECON. & BUS. REV. 205 (2017); Sharon Sutherland, *How boards can use megatrends to chart a new course*, EY (July 23, 2020), https://www.ey.com/en_gl/board-matters/how-boards-can-use-megatrends-to-chart-a-new-course.

use of ML is misplaced. However, Chesterman rightly questions[193] technologically-deterministic arguments that favour the replacement of humans by ML. Such substitutive decisions are themselves likely to be made by humans, taking into account broader social and institutional contexts.[194] Indeed, other scholars[195] have articulated scepticism that substitutive changes of significant degree would occur at companies' corporate governance levels, due to institutional and moral reasons that restrain such choices. At this juncture, it is more imperative than ever for human leadership at Boardrooms to be explicit about the deployment of ML.

B. Enterprise-wide Approach

Consistent with the decentred analysis of governance for ML in economy and society, we suggest that companies should also support an enterprise-wide governance framework for ML within their organisational boundaries, connecting different departments and relevant personnel into internal and 'flat' 'networks' of governance, rather than leaving decisions regarding ML to siloed departments. Such internal organisation mirrors the wider external governance fabric.

Enterprise-wide frameworks[196] are already well-known for risk management.[197] It is often observed that enterprise-wide risk management creates a culture of risk management that is more holistic and able to connect with corporations' wider responsibility[198] and not only with insular notions of shareholder accountability. Another enterprise-wide development that companies may adopt is enterprise-wide responsible innovation. Commentators observe that, as companies grapple with the new risks and opportunities of innovation, enterprise-wide committees are often created in order to integrate business, external and compliance concerns.[199] Indeed

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193 Simon Chesterman, *Artificial Intelligence and the Problem of Autonomy*, 1 NOTRE DAME J. ON EMERGING TECHS. 210 (2020).

194 Kuflik, *supra* note 83; Balkin, *supra* note 115.

195 Iris H.-Y. Chiu & Ernest W.K. Lim, *Technology vs Ideology: How Far will Artificial Intelligence and Distributed Ledger Technology Transform Corporate Governance and Business*?, 18 BERKELEY BUS. L.J. 1 (2021); Alan J. Dignam, *Artificial Intelligence: The Very Human Dangers of Dysfunctional Design and Autocratic Corporate Governance* (Queen Mary Univ. of London, Working Paper No. 314, 2019), https://ssrn.com/abstract=3382342; Luca Enriques & Dirk A. Zetzsche, Corporate Technologies and the Tech Nirvana Fallacy, 72 HASTINGS L.J. 55 (2019).

196 THOMAS H. STANTON, WHY SOME FIRMS THRIVE WHILE OTHERS FAIL: GOVERNANCE AND MANAGEMENT LESSONS FROM THE CRISIS chs. 3, 5 (2012) (on the importance of enterprise-wide frameworks including risk management).

197 *See supra* note 181.

198 CORTEZ, *supra* note 181.

199 Keren Asante, *Richard Owen & Glenn Williamson, Governance of New Product Development and Perceptions of Responsible Innovation in the Financial Sector: Insights from an Ethnographic Case*

enterprise-wide responsible innovation is arguably already a regulatory benchmark in the financial sector. European guidelines[200] explicitly set out how product innovation should be governed in order to mitigate risks of mis-selling, as well as product risks turning into systemic and market risks for financial markets participants.

It may however be argued that companies often integrate ML into enterprise-wide systems as ML's data-processing capabilities facilitate an enterprise-wide approach.[201] In this manner, instead of joined-up human leadership that oversees and reviews ML, even enterprise-wide systems can become technologically-reliant.[202] We urge companies that intend to use and deploy ML in this manner to subject such decisions to the highest level of governance and ongoing oversight. The penetration of ML and reliance on ML for risk and innovation oversight should not result in a gap of discretionary oversight and review after all.[203]

Next, we propose that companies' enterprise-wide frameworks should also incorporate external and stakeholder engagement. Board leadership (perhaps led by the relevant Innovation Committee or the Chief Innovation Officer) should institute processes for external engagement in order to consider feedback when developing internal frameworks for risk management and responsibility.[204] Such external engagement and discourse should be navigated within the thick and broad paradigm of corporate responsibility, seeking multi-stakeholder input and co-governance.[205] These external initiatives should not be instrumental and cosmetic forms of communication or 'washing'. There should be both procedural and substantive implications of such engagement and discourse.

Study, 1 J. RESPONSIBLE INNOVATION 9 (2014).

200 Eur. Banking Auth., *Guidelines on Internal Governance Under Directive 2013/36/EU*, at 45–46 (2017), https://eba.europa.eu/sites/default/documents/files/documents/10180/1972987/eb859955-614a-4afb-bdcd-aaa664994889/Final%20Guidelines%20on%20Internal%20Governance%20(EBA-GL-2017-11).pdf.

201 See, e.g., *Bryan Buck & John Morrow, AI, Performance Management and Engagement: Keeping Your Best Their Best*, 17 STRATEGIC HR REV. 261 (2018).

202 Kenneth A. Bamberger, *Technologies of Compliance: Risk and Regulation in a Digital Age*, 88 TEX. L. REV. 669 (2010).

203 Johnson, *supra* note 83.

204 Katyal, *supra* note 6.

205 Ruth V. Aguilera, Deborah E. Rupp, Cynthia A. Williams & Jyoti Ganapathi, *Putting the S Back in Corporate Social Responsibility: A Multilevel Theory of Social Change in Organizations*, 32 ACAD. MGMT. REV. 836 (2007); Jan Lepoutre, Nikolay A. Dentchev & Aimé Heene, *Dealing with Uncertainties When Governing CSR Policies*, 73 J. BUS. ETHICS 391 (2007).

C. Stakeholders and Gatekeepers

Stakeholder engagement should include meaningful two-way communication such as dialogue and feedback from those that would be affected by the use and deployment of ML.[206] An initial circle of directly affected constituents comprises an internal and external aspect. The internal aspect relates to employees and other workers, while the external aspect relates to constituents such as suppliers and customers, and perhaps regulators.[207] There should be proactive engagement[208] on the part of companies rather than waiting for complaints to arrive. Commentators also suggest that stakeholders affected can also act as gatekeepers, such as technology company employees that influence their companies' policies on innovation in order to avoid social harm.[209] Companies should be willing to treat their stakeholders, both internal and external, as potential gatekeepers in co-governing the development and use of innovation such as ML.

Procedural structures for engagement should not merely be treated as external relations exercises but should be engaged with co-learning opportunities that can have substantive implications, such as shaping the choices that are strategically made by companies in relation to adoption of ML or its risk management. As discussed in Section 2, the deployment of ML entails social, economic and moral consequences beyond initial circles of directly affected stakeholders, and consequences may reverberate in communities. Substantive choices need to be made for example in relation to: the pace of deploying ML and whether stakeholders and communities could catch up with their implications;[210] choices to be made in relation to human agency or oversight and standards of such oversight;[211] and the extent of human accountability in spite of the black box nature of ML.[212] These substantive choices reflect principles in relation to accountability[213] and justice,[214] as well as values embodied in institutions and society,[215] and should be made by companies within a thick and broad paradigm of social

206 Leonard, *supra* note 97.

207 A perspective offered in Caron, *supra* note 62.

208 Bughin & Hazan, *supra* note 18.

209 Jennifer S. Fan, *Employees as Regulators: The New Private Ordering in High Technology Companies*, 5 UTAH L. REV. 973 (2019).

210 WALLACH, *supra* note 18.

211 Chesterman, *supra* note 193; Kuflik, *supra* note 83; Balkin, *supra* note 115.

212 Martin, *supra* note 6.

213 *Id.*

214 Liu, *supra* note 84; Floridi et al., *supra* note 130.

215 *Liability for Artificial Intelligence and Other Emerging Technologies*, *supra* note 80.

responsibility.[216]

The practical proposals for companies above apply to the ML risks discussed in Section 2. Where external and regulatory liability are uncertain, it is imperative that companies do not take advantage of legal uncertainties and gaps to engage in instrumental arbitrage. Such behaviour may prejudice stakeholders' positions, allowing companies to reserve the benefits of innovation and efficiency to themselves, while externalising costs unto stakeholders and society. This could lead to long-term and unexpected reputational and social risks and affect corporations in terms of their social legitimacy.

D. Proactive Management

Companies should aim to proactively manage ML risks, holistically within the corporation and by engaging with multi-stakeholders through communication and education, as discussed above. Companies should also consider appropriate precautionary measures that seek to prevent harm, while being able to experiment with innovations.

A 'precautionary' attitude here is not understood in a sense that promotes risk aversion and avoidance of innovation but as as a willingness to consider the wider values of protection underlying the precautionary ethos. Companies should consider the appropriateness of precautionary preparations in advance of decisions. Such consideration ensures that corporate decisions are not based narrowly on firm-based instrumental calculations of cost and benefit but on an even-handed analysis extending more broadly to business-society relations.[217] It may also be worthwhile for companies and regulators to consider setting particular safe harbours for experimental use and deployment of ML, such as legislative initiatives that have been introduced for self-driving cars.[218] Regulators may also wish to consider instituting ML sandboxes[219] for corporations so that innovation can be carried out within supervised parameters that aim at minimising stakeholder and external harm. The sandbox concept, pioneered in relation

216 Krkač, *supra* note 164; Bughin & Hazan, *supra* note 18.

217 Steve Clarke, Future Technologies, *Dystopic Futures and the Precautionary Principle*, 7 ETHICS & INFO. TECH. 121 (2005).

218 *Self-Driving Cars to Test City Limits*, SCI. AM. (June 1, 2021), https://www.scientificamerican.com/custom-media/pictet/self-driving-cars-to-test-city-limits/. For example, there are designated test zones and roads for self-driving cars in Korea and Beijing.

219 Hagemann et al., *supra* note 178; Bertolini, *supra* note 80.

to the fintech industry,[220] provides a useful regulatory tool for the public and private sectors to engage in co-learning and shaping responsible and socially accountable innovation. However, improvements[221] can be made to the sandbox concept, such as involving multi-stakeholder governance[222] and increasing transparency with regard to the results of sandbox experiments and lessons for corporate strategy and regulatory reform.[223]

E. Prudential Provision

Further, corporations intending to deploy ML should consider making 'prudential' provisions in relation to the risks discussed in Section 2. Even if the laws and regulations are not determinate in respect of liability,[224] corporations could consider compensatory obligations as a matter of social goodwill in relation to the adverse impacts on the stakeholders and communities.[225] A balance of considerations for such goodwill decisions includes: the level of sophistication of stakeholders and communities, whether they are subject to increased risk of harm which they may not be able to manage or diversify easily, and whether benefits to the corporation may be disproportionate compared to the social benefits of innovation. Floridi et al.[226] rightly point out that the deployment of innovation cannot rule out mistakes and accidents. The allocation of burden should be based on a socially-integrated paradigm of corporate responsibility that goes beyond established legal and regulatory doctrines, especially in an emerging area where these regimes have not yet fully caught up. Such prudential provision can jointly be made amongst corporations in the same sector, like

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220 Fin. Conduct Auth., *Regulatory Sandbox* (Nov. 2015); *Default Standards for Sandbox Testing Parameters* (2015), https://www.fca.org.uk/publication/policy/default-standards-for-sandbox-testing-parameters.pdf; Fin. Conduct Auth., *Regulatory Sandbox Lessons Learned Report* (2017), https://www.fca.org.uk/publication/research-and-data/regulatory-sandbox-lessons-learned-report.pdf. The sandbox approach is now adopted in many international jurisdictions. *See* Ross P. Buckley, Douglas Arner, Robin Veidt & Dirk Zetzsche, *Building FinTech Ecosystems: Regulatory Sandboxes, Innovation Hubs and Beyond*, 61 WASH. U. J.L. POL'Y 55 (2019).

221 Such as clarity for sandboxed firms' rights and obligations and competition issues at industry level, discussed in Hilary J. Allen, *Regulatory Sandboxes*, 87 GEO. WASH. L. REV. 579 (2019), and Brian Knight & Trace Mitchell, *The Sandbox Paradox: Balancing the Need to Facilitate Innovation with the Risk of Regulatory Privilege*, 72 S.C. L. REV. (2020).

222 Dirk A. Zetzsche, Ross P. Buckley, Janos N. Barberis & Douglas W. Arner, *Regulating a Revolution: From Regulatory Sandboxes to Smart Regulation*, 23 FORDHAM J. CORP. & FIN. L. 31 (2017).

223 Iris H.-Y. Chiu, *A Rational Regulatory Strategy for Governing Financial Innovation*, 8 EUR. J. RISK REGUL. 743 (2017).

224 *See supra* Section 2.

225 *Liability for Artificial Intelligence and Other Emerging Technologies, supra* note 80; Asaro, *supra* note 78.

226 Floridi et al., *supra* note 130.

an industry initiative. It has also been opined that corporations and their ML suppliers could consider their compensatory liability for harm as a 'common enterprise' responsibility.[227]

F. Transparency

Managing ML risks within a thick and broad paradigm of corporate responsibility also means that corporations should be accountable for how they manage these risks by making appropriate disclosures. It is suggested that ML risks be disclosed as part of mandatory securities disclosure in the US, as certain reporting templates such as 'risk factors' and the Management Discussion and Analysis could be relevant locations for disclosure.[228] On the one hand, such disclosure reform may focus companies on making material disclosure with a financial bent.[229] On the other hand, the expansion of social disclosure in securities disclosure[230] can lead to changes in companies' orientation and culture in treating accountability.[231] There is certainly scope for explicit adoption of mandatory disclosure such as in non-financial disclosure in the UK[232] and EU[233] regarding the risks to stakeholders and communities in relation to the deployment of ML. Pending that development, companies should be encouraged to make voluntary disclosure in their responsibility reports or integrated reports.[234]

It is arguable that voluntary corporate responsibility reporting standards such as the GRI standards[235] have not comprehensively interrogated ML risks and provided for specific disclosures. However, it is also arguable that existing standards can cater somewhat for reporting ML risks, such as in

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227 Vladeck, *supra* note 81.

228 Sylvia Lu, *Algorithmic Opacity, Private Accountability, and Corporate Social Disclosure in the Age of Artificial Intelligence*, 23 VAND. J. ENT. & TECH. L. 99 (2020).

229 The financially driven nature of securities disclosure, see Iris H.-Y. Chiu, *The Paradigms for Mandatory Non-Financial Disclosure: A Conceptual Analysis*, 27 CO. LAW. 259, 291 (2006).

230 Barnali Choudhury, *Social Disclosure*, 13 BERKELEY BUS. L.J. 183 (2016).

231 Iris H.-Y. Chiu, *Unpacking the Reforms in Europe and UK Relating to Mandatory Disclosure in Corporate Social Responsibility: Instituting a Hybrid Governance Model to Change Corporate Behaviour?*, 14 EUR. CO. L. 193 (2017). *But see* Andrew Johnston, *Market-Led Sustainability Through Information Disclosure*, in CAMBRIDGE HANDBOOK OF CORPORATE LAW, CORPORATE GOVERNANCE AND SUSTAINABILITY, *supra* note 151, at ch. 15.

232 Companies Act (U.K.) 2006 c. 46, § 414CA.

233 Directive 2014/95/EU of the European Parliament and of the Council of 22 October 2014 Amending Directive 2013/34/EU as Regards Disclosure of Non-Financial and Diversity Information by Certain Large Undertakings and Groups, 2014 O.J. (L 330/1), art. 19a.

234 Leonard, *supra* note 97.

235 *See* Collection of Global Reporting Initiative (GRI) Standards, GRI, https://www.globalreporting.org/how-to-use-the-gri-standards/gri-standards-english-language/ (last visited June 9, 2021).

relation to 'Management Approach'.[236] Companies that adopt the GRI should disclose key information with regard to the organisation, governance of senior management and frameworks for making decisions, and ML risks can be included. Further, the deployment of ML that may affect occupational health and safety ought to be disclosed[237] and ML deployment can be relevant for disclosure in relation to the training and education of employees.[238] Further, disclosure should be made in relation to customer privacy and data safety.[239] Where ML is deployed to affect local communities, such as Uber's testing of self-driving cars in particular neighbourhoods, adverse impacts should be disclosed.[240]

Nevertheless, the GRI standards can benefit from a better integration of ML risks. For example, the strategic considerations and use of ML at governance and management levels need to be explicitly provided for.[241] The impact on suppliers,[242] customers,[243] job security for employees[244] can also be more clearly articulated. Corporations' stance on innovation and the pace of adoption of ML can also be made accountable under economic disclosures[245] in the GRI standards. Specific impact on sustainability considerations, if any, should be disclosed. The pervasive use of ML in marketing and sales and the risks of behavioural manipulation of customers should also be reflected in the standards regarding marketing and labelling.[246]

In general, corporations should endeavour to engage in more precise accountability to both shareholders and society in relation to their deployment of ML and how they manage the risks depicted in Section 2.

In sum, we propose that corporations should navigate ML risks in a broad and thick paradigm of corporate responsibility in the following ways:

a Institute corporate governance structures for leadership in strategic and responsible decisions regarding ML risk;

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236 Glob. Reporting Initiative, Consolidated Set of GRI Sustainability Reporting Standards 2020, Standard 103 (2020).

237 *Id.* Standard 403.

238 *Id.* Standard 404.

239 *Id.* Standard 418.

240 *Id.* Standard 413.

241 Such as in *id.* 103.

242 *Id.* Standard 414.

243 *Id.* Standard 416, 418.

244 Perhaps under *id.* Standard 401.

245 *Id.* Standard 201.

246 *Id.* Standard 417.

b institute enterprise-wide structures for broad and integrated governance of ML risk internally;
c to engage meaningfully with stakeholders and regulators on the strategic and responsible use of ML and to consider their feedback when designing and implementing internal enterprise-wide structures for managing ML risk;
d to engage in multi-stakeholder governance frameworks integrating the public and private dimensions, in order to participate in the shaping of public policy;
e to make voluntary disclosure of ML risks and management even when not subject to mandatory disclosure;
f to make prudential provision for ML risks in relation to bearing burdens for loss consistent with notions of social justice, fair burden and risk allocation; and
g to actively dialogue with regulators for sandbox arrangements for testing and experimenting with ML so that risks can be observed, and their management can be based on a fully considered and accountable process.

V. CONCLUSION

Corporations are increasingly interested in adopting ML systems in many aspects of their strategic, operational, production and risk management functions in order to enjoy performance enhancement through the data analytic capabilities of ML systems, efficiency savings and competitive advantage. However, corporations seem to be slower to recognize the need to manage the risks of deploying ML systems. This article provides a framework for mapping four key legal and related non-legal risks that need to be managed and argues that in the context of dynamic developments in law and regulation, corporate users of ML systems need an approach for navigating these risks. We provide a blueprint for such an approach, anchored in a widely defined 'corporate responsibility' paradigm that allows corporations to manage their ML risks in an integrated manner, and as a matter of business-society relations. This blueprint incorporates corporations' internal concerns and their external relations. We argue that the applicational implications of our 'corporate responsibility' paradigm are both appropriate and practicable, and we make recommendations for corporations to adopt: governance frameworks, enterprise-wide approaches, prudential provision, broad accountability mechanisms and a networked multi-stakeholder approach to shaping and governing their strategic deployment of ML technologies.