

Managing Corporations' Risk in Adopting Artificial Intelligence: A Corporate Responsibility Paradigm

Iris H-Y Chiu* and Ernest WK Lim**

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 programmes 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 different from the legal risk 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 choices⁹ and even sub-optimal behavioural phenomena,¹⁰ and *who* should be accountable for such risks.¹¹ Extant literature provides rich discussion of these issues, and there are only

*Professor of Corporate Law and Financial Regulation, University College London.

** Associate Professor of Law, National University of Singapore. We are thankful to Sathya Kumar for research assistance.

¹ Gillian Hadfield, 'Rules for Robots: Building Legal Infrastructure for Artificial Intelligence', CEL Biennial lecture, University College London, 18 June 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' (2019) 48 *International Journal of Information Management* 63.

² Eric Siegel, *Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie or Die* (Chichester: John Wiley & Sons 2013).

³ Arif Cam; Michael Chui, Bryce Hall, 'Global AI Survey: AI proves its worth, but few scale impact' (McKinsey Insights, 22 Nov 2019).

⁴ Above.

⁵ Curtis EA Karnow, 'The Application of Traditional Tort Theory to Embodied Machine Intelligence' in Ryan Calo, Michael Froomkin and Ian Kerr (eds), *Robot Law* (Cheltenham: Edward Elgar 2019), ch3.

⁶ Kirsten Martin, 'Ethical Implications and Accountability of Algorithms' (2019) 160 *Journal of Business Ethics* 835; Sonia K Katyal, 'Private Accountability in the Age of Artificial Intelligence' (2019) 66 *UCLA L Rev* 54.

⁷ Contractual error in automated arrangements such as orders placed by Internet of Things machines: Samir Chopra and Laurence White, 'Artificial Agents and the Contracting Problem: A Solution via an Agency Analysis' (2009) 2009 *U Ill JL Tech & Pol'y* 363.

⁸ the fatal accident involving Elaine Herzberg with Uber's self-driving car, 'Fed says self-driving Uber SUV did not recognise jaywalking pedestrian in fatal crash' (7 Nov 2019), <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 Jr Cowger, 'Liability Considerations When Autonomous Vehicles Choose the Accident Victim' (2018) 19 *J High Tech L* 1.

¹⁰ Tim Harford, 'Expect Mischief as Algorithms Proliferate' (Financial Times 22 Feb 2019).

¹¹ Discussions range from manufacturers' product liability, to users' vicarious liability, including for employees, dangerous animals, children etc, to whether autonomous machines should bear their own liability, Eric TL Tjong, 'Liability for (Semi)Autonomous Systems: Robots and Algorithms' (2018), <http://ssrn.com/abstract=3161962>; Ugo Pagallo, *The Laws of Robots: Crimes, Contracts and Torts* (Heidelberg:

emerging regulatory frameworks¹² and soft law in the form of ethical principles¹³ to provide guidance for corporations navigating in this area of innovation. This article focuses on corporations that deploy ML and not as 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 companies' 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 at the level of industry, stakeholders and broader society as governance initiatives are being developed in a number of different 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 with 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 that unpredictable results¹⁴ may occur, 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 unpack in Section 2, namely, (a) risks of external harms and liability; (b) risks of regulatory liability; (c) reputational risks and (d) risks of an operational nature and financial losses that may be significant. These risks do not insularly affect corporations and their shareholders as they often interact with a broader narrative in relation to business-society relations. Indeed, these risk 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 what the 'thick and broad' paradigm of corporate responsibility is.

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

Springer 2013), chs 1, 2, 4 and 5; 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' (2019), <https://law.stanford.edu/publications/no-43-civil-liability-and-autonomous-robotic-machines-approaches-in-the-eu-and-us/>; Andrew Selbst, 'Negligence and AI's Human Uses' (2020) *Boston University Law Review*; Samir Chopra and Laurence F White, *A Legal Theory for Autonomous Artificial Agents* (University of Michigan Press 2011); Shawn Bayern, 'The Implications of Modern Business Entity Law for the Regulation of Autonomous Systems' (2015) 19 *Stanford Technological Law Review* 93.

¹² European General Data Protection Regulation.

¹³ E.g. Partnership on AI, Asilomar Principles, AI4People Principles and the World Economic Forum's ethical guidelines.

¹⁴ Chris Curran & Anand Rao, Briefing: Artificial Intelligence, PWC: NEXT IN TECH (22 Jan. 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' (2019) 88 *Fordham L Rev* 613.

¹⁶ Section 3.

out in a manner more porous to and integrated with social discourse and expectations. 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.

1. Corporations' Adoption of ML

Businesses increasingly deploy artificial intelligence (AI) systems in diverse areas such as finance,¹⁹ healthcare,²⁰ taxation,²¹ sales and marketing,²² production and manufacturing,²³ and risk management.²⁴ There are different definitions of AI but 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 evolves from businesses' adoption of automation, which has started 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 'autonomous' 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 but 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 with statistical

¹⁷ Jannis Kallinikos, *The Consequences of Information: Institutional Implications of Technological Change* (Cheltenham: Edward Elgar 2017).

¹⁸ Wendell Wallach, *A Dangerous Master: How to Keep Technology from Slipping Beyond Our Control* (Basic Books 2015); Jacques Burghin and Eric Hazan, 'Can Artificial Intelligence Help Society As Much As It Helps Business?' *McKinsey Quarterly* (6 Aug 2019).

¹⁹ CL Dunis et al (eds), *Artificial Intelligence in Financial Markets: Cutting-Edge Applications for Risk Management, Portfolio Optimization and Economics* (Palgrave Macmillan, 2016).

²⁰ B Nordlinger et al (eds), *Healthcare and Artificial Intelligence* (Springer, 2020).

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

²² T Davenport et al, "How Artificial Intelligence Will Change the Future of Marketing" (2020) 48 *Journal of the Academy of Marketing Science* 24; P Gentsch, *AI in Marketing, Sales and Service* (Palgrave Macmillan, 2019).

²³ RY Zhong et al, "Intelligent Manufacturing in the Context of Industry 4.0: A Review" (2017) 3 *Engineering* 616; M Klumpp, "Regulation for Artificial Intelligence and Robotics in Transportation, Logistics and Supply Chain Management" (2018) 20 *Network Industries Quarterly* 1.

²⁴ S Aziz and M Dowling, "AI and Machine Learning for Risk Management" in T Lynn et al (eds), *Disrupting Finance: FinTech and Strategy in the 21st Century* (Palgrave, 2019); Federation of European Risk Management Associations (FERMA), *Artificial Intelligence Applied to Risk Management* (2019).

²⁵ European Commission, *A Definition of AI: Main Capabilities and Scientific Disciplines* (2019); M Boden, *AI: Its Nature and Future* (OUP, 2016).

²⁶ Mikell P Groover, 'Automation', an entry in the *Britannica Encyclopedia*, at <https://www.britannica.com/technology/automation>.

²⁷ *Ibid.*

²⁸ Paulius Cerka, Jurgita Grigien, Gintare Sirbikyt, 'Liability for Damages Caused by Artificial Intelligence' (2015) 31 *Computer Law and Security Review* 316.

²⁹ Lior Rokach and Oded Maimon, *Data Mining with Decision Trees: Theory and Applications* (World Scientific, 2008, 2nd ed), <http://repository.fue.edu.eg/xmlui/bitstream/handle/123456789/3632/9792.pdf?sequence=1>.

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 yet far from ‘super intelligence’,³¹ the term used to describe AI able to replicate human intelligence. The development of AI is often discussed in three stages, i.e. narrow AI, general AI and super AI.

Narrow AI refers to the ability of computers to undertake specific tasks, such as by learning the rules of a game such as 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 precise 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 or facial recognition software, but more like an all-rounded android. Recent research exposed in conference proceedings show that there is only incremental development towards building general AI.³⁶ As the developments in communications robotics show,³⁷ general AI seems to be rudimentary. An area of much-hyped development in general AI is that of self-driving cars,³⁸ as self-driving encompasses a

³⁰ Eg Mohammed Abbas Kadhim, M. Afshar Alam, and Harleen Kaur, ‘A Multi-Intelligent Agent for Knowledge Discovery in Database (MIKDD): Cooperative Approach with Domain Expert for Rules Extraction’ in De-Shuang Huang, Kang-Hyun Jo and Ling Wang (eds), *Intelligent Computing Methodologies* (Heidelberg: Springer 2014), 602-614.

³¹ Kaplan and Haenlein (2019).

³² L Thorne-McCarty, ‘Finding the Right Balance in Artificial Intelligence and the Law’ in Woodrow Barfield and Ugo Pagallo (eds), *Research Handbook on the Law of Artificial Intelligence* (Cheltenham: Edward Elgar 2018), ch 3.

³³ Yanqing Duan, John S. Edwards, Yogesh K Dwivedi, ‘Artificial Intelligence for Decision Making in the Era of Big Data – Evolution, Challenges and Research Agenda’ (2019) 48 *International Journal of Information Management* 63.

³⁴ Gillian Hadfield, ‘Rules for Robots: Building Legal Infrastructure for Artificial Intelligence’, CEL Biennial lecture, University College London, 18 June 2019; Arno Lodder, ‘Regulation of Algorithms’, lecture, London School of Economics, 19 June 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’ (2010) 107 *PNAS* 18203, <https://doi.org/10.1073/pnas.1012933107>, different from the holistic and integrated nature of human reasoning, Lodder (2019).

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 and Oleg Baskov, ‘Unsupervised Language Learning in OpenCog’ in Matthew Iklé, Arthur Franz, Rafal Rzepka and Ben Goertzel (eds), *Artificial General Intelligence* (2018), 109-118. However, there is more significant breakthrough in enabling AIs to design, Andreas M. Hein and H’el’ene Condat, ‘Can Machines Design? An Artificial General Intelligence Approach’ in Matthew Iklé, Arthur Franz, Rafal Rzepka and Ben Goertzel (eds), *Artificial General Intelligence* (2018), 87-99.

³⁷ Kotaro Hayashi, Takayuki Kanda, Hiroshi Ishiguro, Tsukasa Ogasawara, and Norihiro Hagita, ‘An Experimental Study of the Use of Multiple Humanoid Robots as a Social Communication Medium’ in Constantine Stephanides (ed), *Universal Access in Human-Computer Interaction* (Heidelberg: Springer 2011), 32-41 on AI mastering passive but not interactive conversation.

³⁸ Google’s subsidiary Waymo has launched a small self-driving taxi fleet in Phoenix, Arizona, ‘Waymo Launches First US Commercial Self-driving Taxi Service’ (5 Dec 2018), <https://www.independent.co.uk/life->

number of different functions that taken together, constitute a complex act of being in control of a motor vehicle. 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 what super AI looks like, in the form of Ava in *Ex Machina*⁴⁰ or a more benign version in 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 laws safeguarding the superiority of humans. 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. It is observed that such adoption is incremental and focused on areas where there is strategic perception of a natural fit between ML and corporations' inclinations to improve efficiency, expand revenue and reduce cost.⁴² We provide a brief survey of corporate adoption of ML below.

First, corporations are attracted to using ML to manage an increasing phenomenon of data volume and overload, such as for compliance or risk management purposes. Human management of voluminous amounts of data can result in error caused by fatigue or negligence, while ML may be able to offer more consistent performance. The question however is whether the performance of ML is comparable to humans in respect of the decision-making or judgment phases of task performance related to 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 may require case-by-case analysis and application.

For example, Deloitte provided a case study of an AI solution developed for its client that analyses the latter's employment tax obligations for the purpose of enabling more effective compliance.⁴³ For a start, the AI model developed by Deloitte is fed with Deloitte's own data such as dictionary, tax laws and regulations, and various training data. Deloitte then works with the client company to locate, extract, clean up and analyse the company's data from

<http://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' (May 2019), <https://www.theverge.com/2018/3/28/17174636/uber-self-driving-crash-fatal-arizona-update>; 'Tesla's Model 3 autopilot mode was activated seconds before a fatal crash' (17 May 2019), <https://www.technologyreview.com/f/613549/teslas-model-3-autopilot-mode-was-activated-seconds-before-a-fatal-crash/>.

⁴⁰ Film released in 2014.

⁴¹ Released in 2010. The laws of robotics are commonly derived from Issac Asimov, *Three Laws of Robotics*, <http://webhome.auburn.edu/~vestmon/robotics.html>.

⁴² Karen Butner and Grace Ho, 'How the Human-Machine Interchange Will Transform Business Operations' (2019) 47 *Strategy and Leadership* 25.

⁴³ Deloitte, "Artificial Intelligence – Entering the World of Tax" (2019), 5.

the company's general ledger, payroll, and accounts payable systems. All the relevant data are then being labelled according to different employment-related expenditure. The AI system is then trained with different sets of scenarios and questions to see if they could provide the correct answers for tax compliance.

However, in autonomous data-management by ML in order for certain judgments to be made, the risks of error and liability entail. There is a risk that sub-optimal outcomes can be attributed to the quality, representativeness and completeness of data,⁴⁴ or the appropriateness of ML routes and pattern-recognition.⁴⁵ In relation to ML systems for bank risk management, commentators have opined that ML is helpful in being able to process complex and voluminous risk data.⁴⁶ However risk data is often backward-looking and not complete. They may capture 'known risks' and 'known unknowns' but often are unable to incorporate 'unknown unknowns'.⁴⁷ In relation to ML systems for financial institutions' implementation of anti-money laundering alert and reporting systems, it is also recognised that the inherent lack of completeness of customer information and changing patterns of financial crime behaviour can severely challenge the essentially data-focused ML systems.⁴⁸ 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 in relation to pattern-recognition capacities that are able to achieve end-to-end functions in a more efficient manner, 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, in particular, involving the internet of things. In global supply chain management, ML is used to analyse demand and sales data in order to manage production, inventories and stock availability.⁴⁹ 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 the hypothetical scenario of managing the supply chain for 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, and these can be automatically processed and transmitted to relevant centers of operations and organisation in the supply chain to trigger production or inventory management.⁵⁰ In such

⁴⁴ TC Redman, "If Your Data is Bad, Your Machine Learning Tools Are Useless" *Harvard Business Review* (2 April 2018); EJ Topol, "High-Performance Medicine: The Convergence of Human and Artificial Intelligence" (2019) 25 *Nature Medicine* 44 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.

⁴⁵ Y Bathaee, "The Artificial Intelligence Black box and the Failure of Intent and Causation" (2018) 31 *Harvard Journal of Law & Technology* 898.

⁴⁶ Udo Milkau and Jürgen Bott, 'Active Management of Operational Risk in the Regimes of the "Unknown": What Can Machine Learning or Heuristics Deliver?' (2018) 6 *Risks* 41.

⁴⁷ Ibid; also F.X. Diebold, N. Doherty, and R.J. Herring (eds.), *The Known, The Unknown and The Unknowable in Financial Risk Management* (Princeton University Press, 2010).

⁴⁸ Accenture, *Evolving AML Journey* (2017), https://www.accenture.com/_acnmedia/pdf-61/accenture-leveraging-machine-learning-anti-money-laundering-transaction-monitoring.pdf.

⁴⁹ Karen Kim, 'Artificial Intelligence in Supply Chain Management' (19 July 2019), <https://www.project-disco.org/innovation/071919-artificial-intelligence-in-supply-chain-management/#.XTdKSW9KiCR>.

⁵⁰ Jen Clark, 'What is the Internet of Things?' (2016), <https://www.ibm.com/blogs/internet-of-things/what-is-the-iot/>.

deployment, ML systems may minimise errors that humans commit 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.⁵¹

However, such supply chain management relies on the predictive analytics capabilities of ML, especially in relation to consumer demand levels, and it remains uncertain if such systems can be resilient against unexpected exogenous shocks to consumer sentiment, such as during the Covid-19 crisis 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.⁵²

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.⁵³ ML may be used to scan employee expense claims, communications, emails etc to detect fraud or abuse. Although this may reduce operational risk and cost for companies, it also raises certain legal and ethical issues in relation 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.⁵⁴ McKinsey⁵⁵ 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'. An 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 more accuracy and at a faster pace.⁵⁶ 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 in order to create customer segmentation. Intel fed millions 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 include but are not limited to thousands of company sites appearing in Wikipedia. The data are labeled by Intel according to two categories, i.e. 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 web but from

⁵¹ Kim (2019).

⁵² Arif Cam; Michael Chui, Bryce Hall, 'Global AI Survey: AI proves its worth, but few scale impact' (McKinsey Insights, 22 Nov 2019).

⁵³ Peter Buell Hirsch, 'Tie Me to the Mast: Artificial Intelligence & Reputation Risk Management' (2018) 39 *Journal of Business Strategy* 61.

⁵⁴ Eric Siegel, *Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie or Die* (Chicester: John Wiley & Sons 2013).

⁵⁵ Cam et al (2019).

⁵⁶ I Lieder et al, "Learning a Faceted Customer Segmentation for Discovering New Business Opportunities at Intel", 2019, <https://arxiv.org/pdf/1912.00778.pdf>.

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 companies surveyed to achieve superior revenue growth.⁵⁷ 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 is incrementally integrated into recruitment and hiring in order to detect talent, productive and unproductive characteristics, so that companies may have a better chance to avoid productivity losses in due course.⁵⁸ Such deployment inevitably raises issues of ethics, discrimination and privacy.⁵⁹ Predictive analytics is also used extensively in credit decisions, especially by fintechs using algorithmic credit scoring and decision-making processes.⁶⁰ The extensive issues in profiling, discrimination, financial inclusion/exclusion, ethics and privacy are discussed at length by commentators.⁶¹

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.⁶² Efficiencies achieved, efforts or errors minimized and revenue growth may be attractive, but companies run inherent risks with ML systems and accompanying risks such as legal, regulatory and reputational.⁶³ Section 2 explores the landscape of risks for corporations considering or are presently adopting ML and argues ultimately that besides targeted regulatory⁶⁴ and external ethical approaches,⁶⁵ an internally-robust 'corporate responsibility' framework is crucial for corporations to manage the risks of adopting ML systems.

2. Mapping the Landscape of Risks for Corporations Adopting ML Systems

⁵⁷ Eric T Bradlow, Manish Gangwar, Praveen Kopalle and Sudhir Voleti, 'The Role of Big Data and Predictive Analytics in Retailing' (2017) 93 *Journal of Retailing* 79.

⁵⁸ Jac Fitz-enz and John R Maddox II, *Predictive Analytics for Human Resources* (Chicester: Wiley & Sons, 2014).

⁵⁹ Wallach (2015).

⁶⁰ J Maguire, "12 Examples of Artificial Intelligence: AI Powers Business" *Datamation* (13 Sep 2019); Mirka Snyder Caron, 'The Transformative Effect of AI on the Banking Industry' (2018) 34 *Banking and Finance Law Review* 169.

⁶¹ Katja Langenbucher, 'Responsible A.I.-based Credit Scoring – A Legal Framework' (2020) 31 *European Business Law Review* 527; Nikita Aggarwal, 'The Norms of Algorithmic Credit Scoring' (2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3569083.

⁶² Andrea Bonime-Blanc, 'Technology, Trust and Ethics: An Actionable Governance Toolkit for a Disruptive Time' (*Carrier Management*, 11 Oct 2018).

⁶³ Hirsch (2018), Sect 2.

⁶⁴ The General Data Protection Regulation addresses some aspects of algorithmic profiling and data subjects' right of challenge, Art 22; 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' (2019) 363 (6429) *Science* 810.

⁶⁵ The development of ethical standards by the EU, Asilomar Conference, OECD and AI4People group, Section 2.

Corporations have been pioneers in adopting technological innovations in production, service, operations, distribution and delivery,⁶⁶ battling legal risks along the way.⁶⁷ Non-human innovative installations have given rise to legal issues decades ago as courts judge new boundaries of rights and obligations, e.g. in the 1970s case regarding the introduction of unmanned automated parking facilities in *Thornton v Shoe Lane Parking Ltd.*⁶⁸ 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.⁶⁹

In this Section, we map 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.⁷⁰ As the strategic adoption of ML systems is a global phenomenon for many 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, 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 argue that an overarching framework that guides and is not mired in jurisdiction-based detail would be useful for 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 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.

Legal Risks

In this part, we deal with the legal risks faced by corporations adopting ML systems in relation to private liability, as a dedicated part is reserved for discussing regulatory risks. There are at least two types of private liability relating to ML systems: commercial and third-party. On the former, corporations deploying ML may face contractual liability risks if the performance of ML affects their contractual performance. There is the possibility that corporations mindful of the novelties in adopting ML systems would seek to manage

⁶⁶ Mark Casson and Catherine Casson (eds), *History of Entrepreneurship: Innovation and Risk-taking, 1200–2000* (Cheltenham, Edward Elgar, 2013); William Lazonick, 'The Innovative Firm' and Alice Lam, 'Organisational Innovation' in Jan Fagerberg and David C. Mowery (eds), *The Oxford Handbook of Innovation* (Oxford: OUP 2006).

⁶⁷ Eg Richard E Epstein, 'Legal Liability for Medical Innovation' (1986-7) 8 *Cardozo Law Review* 1139.

⁶⁸ [1971] QB 163 on whose responsibility it is to draw the consumer's attention to onerous terms in an unmanned automated parking facility.

⁶⁹ Michael Callier and Harly Callier, 'Blame It on the Machine: A Socio-Legal Analysis of Liability in an AI World' (2018) 14 *Wash J L Tech & Arts* 49.

⁷⁰ Cam et al (2019).

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.⁷¹ However, this may be more unpredictable if a consumer is involved.⁷² In terms of third-party liability, corporations deploying ML systems may incur private liability if harm, such as physical injury is caused to third parties, such as where a self-driving car runs into a pedestrian.⁷³ Private liability may also be incurred if economic losses are occasioned to third parties, where relationships of proximity⁷⁴ 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 on 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 be regarded as personally liable instead,⁷⁵ the consequence being that normative jurisprudence should move away from fault and responsibility⁷⁶ on the part of the deployer of ML systems? In this manner, we

⁷¹ Sections 2, 3, UK Unfair Contract Terms Act 1977; Uniform Commercial Code s2-316; Tod M. Turley, Expert Software Systems: The Legal Implications, 8 Computer L.J. 455, 457 (1988); Roland B. Desilets, Jr., Note, Software Vendors' Exposure to Products Liability for Computer Viruses, 9 Computer L.J. 509, 524 (1989). cited in Maruerite E. Gerstner, Liability Issues with Artificial Intelligence Software, 33 Santa CLARA L. REV. 239 (1993), 254, 262.

⁷² Consumers are protected under the UK Consumer Rights Act 2015 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 opinion based in the EU, Przemysław Pałka, Agnieszka Jabłonowska, Hans-W. Micklitz and Giovanni Sartor, 'Before Machines Consume the Consumers' (EUI Working Paper 2018), <https://ssrn.com/abstract=3228085>.

⁷³ Eg Uber's self-driving car's accident that killed a pedestrian in Arizona, 'Uber won't be charged with fatal self-driving' (5 March 2019, the verge.com). However, for a contrary opinion in the EU (focusing on UK and Germany), see Michael Chatzipanagiotis & George Leloudas, Automated Vehicles and Third-Party Liability: A European Perspective, 2020 U. ILL. J.L. TECH. & POL'y 109 (2020).

⁷⁴ *Caparo Industries PLC v Dickman* [1990] UKHL 2. 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).

⁷⁵ Shawn Bayern and Thomas Burri and Thomas D Grant and Daniel M Hausermann and Florian Möslein and Richard Williams, 'Company Law and Autonomous Systems: A Blueprint for Lawyers, Entrepreneurs, and Regulators' (2017) 9 Hastings Sci & Tech LJ 135; Iria Giuffrida, 'Liability for AI Decision-Making: Some Legal and Ethical Considerations', 88 Fordham L. Rev. 439, 440 (2019).

⁷⁶ Peter M Asaro, 'The Liability Problem for Autonomous Artificial Agents' (2016) Conference paper for Association for the Advancement of Artificial Intelligence 190.

would focus only on restoring or compensating the victim, moving away from doctrinal analyses of human ‘fault’ or ‘responsibility’.⁷⁷ Commentators have suggested that third-party harms entailing from the deployment of ML systems could be compensated by a pre-funded institution⁷⁸ that pays for the social cost of innovation or by insurance arrangements.⁷⁹ Such normative ideas have traction especially if we consider the scenario of the 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, so that innovation can be facilitated.⁸⁰ 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,⁸¹ and both ethical and legal interrogation⁸² must take place as innovation becomes socially accepted. This argument is more ‘coherentist’ in nature, as according to Brownsword,⁸³ 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 normatively-led law reforms.

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?⁸⁴ The deployment of ML that is 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 take

⁷⁷ This is opposed in F. Patrick Hubbard, *Sophisticated Robots: Balancing Liability, Regulation, and Innovation*, 66 FLA. L. REV. 1803 (2014).

⁷⁸ Andrea Bertolini, ‘Insurance and Risk Management for Robotic Devices: Identifying the Problems’ (2016) 16 *Global Jurist* 291; Giuffrida (2019); European Commission Expert Group on Liability and New Technologies, *Liability for Artificial Intelligence and Other Emerging Technologies* (2019).

⁷⁹ Woodrow Barfield, ‘Liability for Autonomous and Artificially Intelligent Robots’ (2018) 9 *J Behav. Robotics* 193; David C Vladeck, ‘Machines Without Principals: Liability Rules and Artificial Intelligence’ (2014) 89 *Washington Law Review* 117.

⁸⁰ Bryan H Choi, ‘Crashworthy Code’ (2019) 94 *Washington Law Review* 39.

⁸¹ Deborah G Johnson, ‘Technology with No Human Responsibility?’ (2015) 127 *Journal of Business Ethics* 707; Arthur Kuflik, ‘Computers in Control: Rational Transfer of Authority or Irresponsible Abdication of Autonomy?’ (1999) 1 *Ethics and Information Technology* 173.

⁸² Hin Yan Liu, ‘Irresponsibilities, Inequalities and Injustice for Autonomous Vehicles’ (2017) 19 *Ethics, Information and Technology* 193.

⁸³ Roger Brownsword, *Law, Technology and Society* (Oxford: Routledge 2019), pp154.

⁸⁴ Curtis EA Karnow, ‘The Application of Traditional Tort Theory to Embodied Machine Intelligence’ in Ryan Calo, A. Michael Froomkin and Ian Kerr (eds), *Robot Law* (Cheltenham: Edward Elgar 2016), ch3; Andrew Selbst, ‘Negligence and AI’s Human Uses’ (2020) *Boston University Law Review* forthcoming.

back control only if requested by the car or in exceptional situations, then the duty of care will 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 questioned what difficulties the autonomous nature of ML decision-making would pose for such positive application of law.⁸⁵ Bathaee⁸⁶ for instance argues that causation concepts need to be reformed in order to capture more holistically the frameworks of human agency in relation to ML operations, so that proximity for causation can be extended.⁸⁷ For example, for highly autonomous ML systems, human agency in design or higher-level frameworks of operation should be regarded as causally proximate. Casey⁸⁸ 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 interrogate how positive applications of law would apply to harms caused by ML systems, product liability of the ML system is often in question and extensively commented on.⁸⁹ Relying on product liability as the doctrinal destination for attribution of compensatory liability⁹⁰ may become a norm, but this is undesirable as product liability is yet another body of law that needs to be interrogated in order for ML systems to fit in.⁹¹ Further, such a distribution of legal risk can be an impediment to innovative companies, especially small or medium sized enterprises.⁹²

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 need to be fashioned. Pedestrian jaywalkers can be regarded as contributorily negligent although drivers are expected to brake and slow down too ahead of the accident. However, are pedestrian jaywalkers contributorily negligent if an approaching

⁸⁵ Bertolini (2016); Liu (2017); Barfield (2018); European Commission (2019).

⁸⁶ Yavar Bathaee, "The Artificial Intelligence Black box and the Failure of Intent and Causation" (2018) 31 Harvard Journal of Law & Technology 898.

⁸⁷ Opitz (2019).

⁸⁸ Bryan Casey, 'Robot Ipsa Loquitur' (2019) 108 Geo LJ 225.

⁸⁹ Gerhard Wagner, 'Robot, Inc.: Personhood for Autonomous Systems?', 88 Fordham L. Rev. 591, 592 (2019); Woodrow Barfield, 'Liability for Autonomous and Artificially Intelligent Robots' (2018) 9 J Behav. Robotics 193; David C Vladeck, 'Machines Without Principals: Liability Rules and Artificial Intelligence' (2014) 89 Washington Law Review 117. 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. 123 (1981).

⁹⁰ the UK class action against Tesla was settled, "Tesla agrees to settle class action over Autopilot billed as 'safer'" (7 Feb 2018), <https://uk.reuters.com/article/uk-tesla-autopilot-lawsuit/tesla-agrees-to-settle-class-action-over-autopilot-billed-as-safer-idUKKCN1IQ1SR>.

⁹¹ Barfield (2018); Vladeck (2014); on the uncertainties in the UK's position, Ernest WK Lim and Iris H-Y Chiu, 'Liability Issues in the Sales of Artificial Intelligence Systems: The B2B Transactional Context and English Private Law' (2020), under consideration.

⁹² Choi (2019).

self-driving car mis-classifies the pedestrian wrongly and accelerates or fails to slow down in advance of the accident?⁹³

The interrogation of ML risks within private law precepts in relation 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 self-driving cars and IBM's Watson 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 the society in ensuring that their development and deployment of ML systems do not create social externalities and instead create social benefits that exceed social harm.⁹⁴ As such, we cannot stop at merely analysing whether and how private law should be reformed to minimise and deter such social harms. The 'social licence to operate' can affect how positive and normative legal conceptions should be shaped, and corporations need to be responsive to this.⁹⁵ Companies can become practically '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.⁹⁶

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,⁹⁷ or implications for legal certainty and how these shape future corporate behaviour. This narrow approach needs to be avoided in relation to corporate deployment of ML risks not least because the positive and normative developments of private law are dynamic, but that such dynamism is driven by underpinning socio-legal narratives about the fairness, social acceptability and legitimacy of ML deployment by corporations.

Regulatory Risks

The deployment of ML systems by corporations entails regulatory risks in three ways. First, 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

⁹³ 'Uber's self-driving car didn't malfunction, it was just bad' (24 May 2018), <https://www.theatlantic.com/technology/archive/2018/05/ubers-self-driving-car-didnt-malfunction-it-was-just-bad/561185/>.

⁹⁴ Palka et al (2018).

⁹⁵ Peter G Leonard, 'Social Licence and Digital Trust In Data-Driven Applications and AI: A Problem Statement and Possible Solutions' (2019) at <https://ssrn.com/abstract=3261228>.

⁹⁶ Kieren Moffat, Justine Lacey, Airong Zhang and Sina Leipold, 'The Social Licence to Operate: A Critical Review' (2016) 89 *Forestry* 477; Melanie (Lain) Dare, Jackie Schirmer and Frank Vanclay, 'Community Engagement and Social Licence to Operate' (2014) 32 *Impact Assessment and Project Appraisal* 188.

⁹⁷ Ernest Weinrib, *The Idea of Private Law* (1995); Jacob Eisler, "The Limits and Promise of Instrumental Legal Analysis" (2020) *Journal of Law and Society*. Cf Richard Posner, *The Economics of Justice* (HUP, 1981).

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,⁹⁸ and these can differ amongst different jurisdictions corporations are operating in. Where ML systems are intended to facilitate more efficient compliance,⁹⁹ 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 important in anti-money laundering compliance in the financial sector, or the use of robo-advisors to provide investment recommendations for financial customers.¹⁰⁰ 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.¹⁰¹ 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,¹⁰² or in customer due diligence and raising of alerts to comply with anti-financial crime¹⁰³ 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,¹⁰⁴ 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 doubted whether regulatory compliance obligations can be perfectly transposed onto the modalities of software.¹⁰⁵ On the other hand, automating compliance also raises behavioural issues for firms in failing to culturally embed the spirit of compliance. Firms need to beware of a form of behavioural 'auto-pilot' where their staff become over-reliant on ML systems and fail to adhere to the spirit of the regulation.¹⁰⁶

⁹⁸ Eg Senthil Selvaraj, 'The Skinny- on How Narrow AI Will Affect Banks' (2019) 101 *The RMA Journal* 42 (6 March 2019).

⁹⁹ Andrea Falcione, 'Taking Corporate Compliance Programs Digital' (2019) *National Defence* 58.

¹⁰⁰ Such as robo-advice, Tom Baker; Benedict Dellaert, 'Regulating Robo Advice across the Financial Services Industry' (2018) 103 *Iowa L. Rev.* 713; Facundo Abraham, Sergio L Schmukler and José Tessada, 'Robo-Advisors: Investing through Machines' (World Bank Research and Policy Brief 2019).

¹⁰¹ Iris H-Y Chiu, 'Transforming the Financial Advice Market - The Roles of Robo-advice, Financial Regulation and Public Governance in the UK' (2019) 35 *Banking and Finance Law Review* 9.

¹⁰² Eg Art 25, EU Markets in Financial Instruments Directive 2014/65/EU, UK Financial Conduct Authority's Handbook COBS 9 and 9A.

¹⁰³ Eg Chapter II, EU Anti-money Laundering Directive 2015/849/EU, amended in 2019, UK Money Laundering Regulations 2017, Part 3, amended in 2019.

¹⁰⁴ Ralf Huber, 'Making Regulation Machine Readable' in Janos Barberis Douglas W. Arner Ross P. Buckley (eds), *The Regtech Book* (Chicester: John Wiley & Sons, 2019), ch26.

¹⁰⁵ James Grimmelman, *Regulation by Software*, 114 *YALE L.J.* 1719 (2005).

¹⁰⁶ Kenneth A Bamberger, "Technologies of Compliance: Risk and Regulation in a Digital Age" (2009/10) 88 *Texas Law Review* 669.

Next, the risks of data collection and management by corporations that deploy ML systems have been widely canvassed.¹⁰⁷ 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 such as whether the right to be forgotten applies to data fed into ML systems, and how this would affect the matrix of information and the learning routes implemented by ML systems.¹⁰⁸ 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.¹⁰⁹ These risks would likely require an enterprise-wide approach on the part of corporations to address them, including the data compliance, risk management and 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.¹¹⁰ 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, financial etc sectors.¹¹¹ However, this is an emerging development and corporations must be prepared for policy changes that can 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.¹¹² In this spirit, corporations cannot merely wait for or rely on regulatory parameters to shape the boundaries of their behaviour but should 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 deterministic¹¹³ 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.

¹⁰⁷ Jim Shook and Robyn Smith and Alex Antonio, 'Transparency and Fairness in Machine Learning Applications' (2018) 4 Tex A&M J Prop L 443; Margot E. Kaminski, 'The Right to Explanation, Explained' 34 Berkeley Tech. LJ 189 (2019); Shlomit Yanisky-Ravid and Sean K Hallisey, 'Equality and Privacy by Design: A New Model of Artificial Intelligence Data Transparency via Auditing, Certification, and Safe Harbor Regimes' (2019) 46 Fordham Urb LJ 428.

¹⁰⁸ 'Machine Unlearning: Fighting for the Right to Be Forgotten' (2 May 2020), <https://syncedreview.com/2020/02/05/machine-unlearning-fighting-for-the-right-to-be-forgotten/>.

¹⁰⁹ N61.

¹¹⁰ Callier and Callier (2018); European Commission Expert Group on Liability and New Technologies, *Liability for Artificial Intelligence and Other Emerging Technologies* (2019).

¹¹¹ Eric TL Tjong, 'Liability for (Semi)Autonomous Systems: Robots and Algorithms' (2018) at <http://ssrn.com/abstract=3161962>.

¹¹² European Commission (2019).

¹¹³ Horst Eidenmüller, 'Machine Performance and Human Failure: How Shall We Regulate Autonomous Machines?' (2019) 15 U of Maryland Journal of Business and Technology Law 109; Jack M Balkin, 'The Three Laws of Robotics in the Age of Big Data' (2017) 78 Ohio State University Law Journal CHK, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2890965.

Corporations are also likely to be involved with regulators, stakeholders, industry and others in the shaping of future regulatory regimes.¹¹⁴ The capacity to engage in policy discourse is an area that corporations should invest in, and this is likely to be best developed in an enterprise-wide manner, involving personnel from strategic, operational, innovation, risk management and compliance departments.

Reputational Risks

Reputational risks for corporations deploying ML systems can arise in two ways, and 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.¹¹⁵ Cambridge Analytica has since been wound up and social trust in Facebook dipped significantly.¹¹⁶ 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.¹¹⁷

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 software¹¹⁸ and algorithmic credit scoring¹¹⁹, the reputation of companies will be adversely affected.¹²⁰ 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.¹²¹ Are corporations deploying ML systems insularly for their own

¹¹⁴ A general trend towards 'co-regulation' is proposed by Michèle Finck, 'Digital Co-Regulation: Designing a Supranational Legal Framework for the Platform Economy' (2018) 43 *European Law Review* 47.

¹¹⁵ 'Cambridge Analytica and Facebook: The Scandal and the Fallout So Far' (4 April 2018), <https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html>; 'The scant science behind Cambridge Analytica's controversial marketing techniques' (*Nature*, 29 March 2018), <https://www.nature.com/articles/d41586-018-03880-4>.

¹¹⁶ 'Trust in Facebook has dropped by 66 percent since the Cambridge Analytica scandal' (11 April 2018), <https://www.nbcnews.com/business/consumer/trust-facebook-has-dropped-51-percent-cambridge-analytica-scandal-n867011>.

¹¹⁷ 'UK to create regulator to police big tech companies' (*Financial Times* 29 Dec 2019), <https://www.ft.com/content/67c2129a-2199-11ea-92da-f0c92e957a96>; 'The World Wants More Tech Regulation' (15 Jan 2020), <https://www.usnews.com/news/best-countries/articles/2020-01-15/the-world-wants-big-tech-companies-to-be-regulated>.

¹¹⁸ Sarah Chun, 'Facial Recognition Technology: A Call for the Creation of a Framework Combining Government Regulation and a Commitment to Corporate Responsibility' (2020) 21 *NC JL & Tech* 99.

¹¹⁹ Langenbucher (2020); Aggarwal (2020).

¹²⁰ Brookings Institution, 'Public Opinion Lessons for AI Regulation' (10 Dec 2019), <https://www.brookings.edu/research/public-opinion-lessons-for-ai-regulation/>; Mark Latonero, 'Governing Artificial Intelligence: Upholding Human Rights & Dignity' (2018), <https://apo.org.au/sites/default/files/resource-files/2018-10/apo-nid196716.pdf>.

¹²¹ 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.

benefit without any consideration of how such deployment promote the long-term trust between business and society? For example, Chun's 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 involves 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?¹²² Where companies deploying ML become intimately involved with their customers, suppliers, stakeholders etc through possession and processing of their data,¹²³ 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 manipulation¹²⁴ (but there is also evidence of ML systems being used to forestall mis-selling led by humans).¹²⁵ Further, corporate reputation may also be undermined where ML systems disrupt work patterns and the political economy, a key aspect of business-society relations.¹²⁶ 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.¹²⁷

Corporations should be cognisant of their share of contribution to social disruptions, upheaval or disorientation, in adopting and deploying ML systems in such a manner that affects their interface with the public and society. Indeed corporations should consider their role in beneficence,¹²⁸ 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,¹²⁹ and the trade-off between efficiency and autonomy, such as in the Internet of Things industry.¹³⁰

¹²² Chun (2020).

¹²³ Natania Locke and Helen Bird, 'Perspectives on the Current and Imagined Role of Artificial Intelligence and Technology in Corporate Governance Practice and Regulation' (2019), <https://ssrn.com/abstract=3534898>; Chopra and White (2011), ch1.

¹²⁴ Palka et al (2018) on how consumers may be unduly influenced and develop technology-dependencies.

¹²⁵ 'Banks employ AI to forestall mis-selling' (16 Feb 2020), https://www.koreatimes.co.kr/www/biz/2020/02/126_283373.html.

¹²⁶ Mona Sloane, 'Making artificial intelligence socially just: why the current focus on ethics is not enough' (LSE Blogs, 6 July 2018), <https://blogs.lse.ac.uk/politicsandpolicy/artificial-intelligence-and-society-ethics/>.

¹²⁷ Michael R Siebecker, 'Making Corporations More Humane Through Artificial Intelligence' (2020) 45 *Journal of Corporation Law* 96.

¹²⁸ The first of the ethical principles proposed by the AI4People group, see Floridi et al (2018).

¹²⁹ Chris Fleissner, 'Inclusive Capitalism Based on Binary Economics and Positive International Human Rights in the Age of Artificial Intelligence' (2018) 17 *Wash U Global Stud L Rev* 201; Kathleen Wilburn and Ralph Wilburn, 'Challenges for Managing Business with 21st Century Technology' (2018) 9 *Review of Business and Finance Studies* 13.

¹³⁰ Tom Allen and Robin Widdison, 'Can Computers Make Contracts' (1996) 9 *Harv J L & Tech* 25; Chopra and White (2011), ch4.

Operational and Financial Losses

Although ML systems have much to offer corporations in terms of performance enhancement, efficiency saving and risk management improvement, 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 such an example.¹³¹ 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 an 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' 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.¹³²

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 the malfunction or substandard ML systems depends on whether they can successfully sue the sellers/suppliers, primarily on the basis of product liability, which as earlier mentioned, raises 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.¹³³ 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 has implications for the questions of satisfactory quality under the SGA as well as contributory negligence under the SGSA.¹³⁴ Further, exclusions of liability may also be effective between

¹³¹ 'Investor Sues Company Over Artificial Intelligence Advice' (28 May 2019), <https://mytechdecisions.com/compliance/investor-sues-company-over-artificial-intelligence-advice/>.

¹³² <https://gdpr.eu/fines/>.

¹³³ Ernest WK Lim and Iris H-Y Chiu, "Liability Issues in the Sales of Artificial Intelligence Systems: The B2B Transactional Context and English Private Law" (forthcoming).

¹³⁴ *Ibid.*

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, the ‘flash crashes’¹³⁵ 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 particular 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 need 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 entailing 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.

3. 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 cater for the transnational and socio-legal character of corporations’ unique risk management needs where ML deployment is concerned.

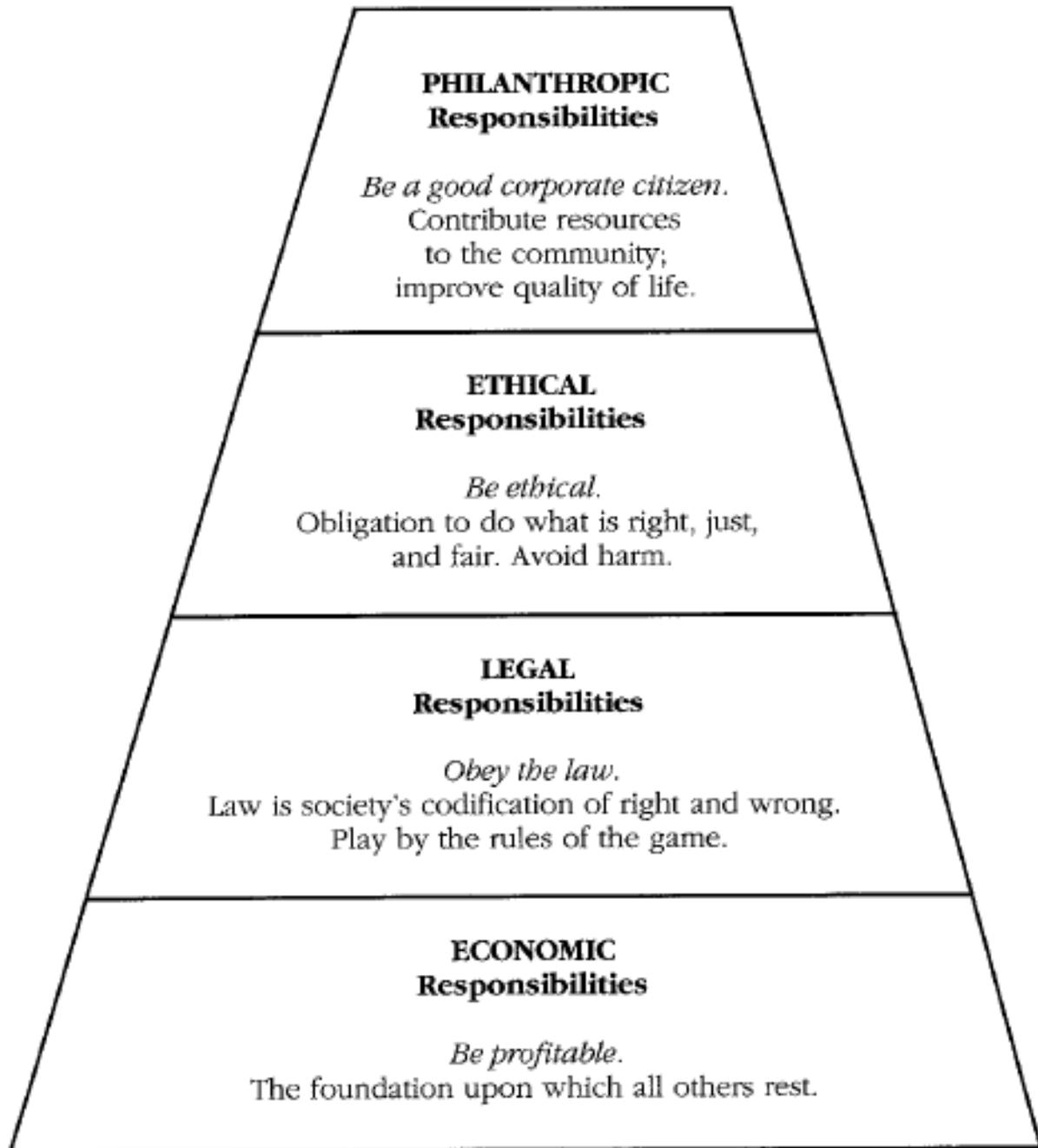
Carroll’s pyramid of corporate social responsibility has often been the starting point for explaining the holistic nature of corporations’ ‘responsibility paradigm’.¹³⁶ Corporations may be primarily responsible for economic production and wealth generation, but they are also

¹³⁵ ‘Flash crashed explained’, <https://www.ig.com/sg/trading-strategies/flash-crashes-explained-190503>.

¹³⁶ Archie B Carroll, ‘The Pyramid of Corporate Social Responsibility: Toward the Moral Management of Organisational Stakeholders’ *Business Horizons* 39 (1991).

nested within a paradigm of external expectations in relation to its citizenship,¹³⁷ including philanthropy. Corporations may be steered by frameworks of law and regulation provide boundaries for behaviour, but they are also situated within a fabric of social expectations and community values and norms beyond what is legalised.¹³⁸

The Pyramid of Corporate Social Responsibility



¹³⁷ Hazel Henderson, 'Transnational Corporations and Global Citizenship' (2000) 43 *American Behavioral Scientist* 1231; Andrew Crane, Dirk Matten and Jeremy Moon, *Corporations and Citizenship* (Cambridge: CUP 2008), ch1.

¹³⁸ John Douglas Bishop, 'For-Profit Corporations in a Just Society: A Social Contract Argument Concerning the Rights and Responsibilities of Corporations' (2008) 18 *Business Ethics Quarterly* 191; Thomas Donaldson, *Corporations and Morality* (Prentice Hall 1982), ch3.

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 management¹³⁹ nor the perverse incentives surrounding an instrumental approach to legal compliance.¹⁴⁰ 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', being an interdisciplinary combination of norms, values, socio-legal, policy and governance perspectives.¹⁴¹

There are increasing calls to corporations deploying ML systems to adhere to ethical principles.¹⁴² The slowness of legal and regulatory policy in articulating particular standards of conduct reflects complex discourse in this area,¹⁴³ 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 is a proliferation of ethical principles from various international bodies, think tanks and voluntary groups. In this respect, corporations should consider whether they should issue their own ethical codes?¹⁴⁴ Should relevant sectors develop industry codes, such as the IEEE's Code?¹⁴⁵ Or are principles and codes issued by stakeholder or other expert groups, such as the Asilomar Principles¹⁴⁶ and the AI4People Principles more credible as representing the terms that societies have negotiated with businesses?¹⁴⁷

¹³⁹ René Stultz, 'Risk Management Failures: What Are They and When Do They Happen?' (2008) 20 *Journal of Applied Corporate Finance* 58 specifically on such application of risk management in the financial sector; Douglas Hubbard, *The Failure of Risk Management: Why It's Broken and How Do we Fix it?* (Chichester: John Wiley & Sons, 2009), chapters 8 and 9.

¹⁴⁰ Christine E. Parker, Robert Eli Rosen and Vibeke Lehmann Nielsen, 'The Two Faces of Lawyers: Professional Ethics and Business Compliance With Regulation' (2009) 22 *Georgetown Journal of Legal Ethics* 201.

¹⁴¹ 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 *Journal of Business Ethics* 1 (1983); Jerry D. Goodstein and Andrew C. Wicks, 'Corporate and Stakeholder Responsibility: Making Business Ethics a Two-Way Conversation' 17 *Business Ethics Quarterly* 375 (2007).

¹⁴² Weforum, 'Top 9 ethical issues in artificial intelligence' (21 Oct 2016), <https://www.weforum.org/agenda/2016/10/top-10-ethical-issues-in-artificial-intelligence/>.

¹⁴³ Eg see European Commission (2019).

¹⁴⁴ E.g Google's Principles on AI, <https://ai.google/principles/>; IBM, 'The code of ethics for AI and chatbots that every brand should follow' (15 Oct 2017), <https://www.ibm.com/blogs/watson/2017/10/the-code-of-ethics-for-ai-and-chatbots-that-every-brand-should-follow/>.

¹⁴⁵ Institute of Electrical and Electronic Engineers' Standards on AI, see 'The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems.'

¹⁴⁶ <https://futureoflife.org/ai-principles/>.

¹⁴⁷ 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' (2018) 28 *Minds and Machines* 689.

The above analysis advances our argument that corporations' 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 primarily to cater for public relations.¹⁴⁸ 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.

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 Sjøfæll and Bruner's¹⁴⁹ 'thick' conception of sustainability, explained as integrating the 'social foundation' upon which corporations operate, and not merely having a peripheralised notion of external consciousness. In their notion which is focused on sustainability, Sjøfæll and Bruner argue that corporations are not insular entities and are operating within a context in relation to the planetary boundaries of the earth's environmental and eco-systems¹⁵⁰ and in relation to public goods such as the UN Sustainable Development Goals.¹⁵¹ 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, that in the context of ML deployment which can pervasively and significantly impact on 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.¹⁵² 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,¹⁵³ or regarded as simply a voluntary management tool¹⁵⁴ or stakeholder-relations exercise,¹⁵⁵ or charitable activities.

¹⁴⁸ To be discussed shortly.

¹⁴⁹ Beate Sjøfæll and Christopher Bruner, 'Corporations and Sustainability' in Beate Sjøfæll and Christopher Bruner (eds), *The Cambridge Handbook of Corporate Law, Corporate Governance and Sustainability* (Cambridge: CUP 2019), ch1.

¹⁵⁰ The nine planetary boundaries explained by the Stockholm Resilience Center, <https://www.stockholmresilience.org/research/planetary-boundaries/planetary-boundaries/about-the-research/the-nine-planetary-boundaries.html>.

¹⁵¹ the 17 sustainable development goals at <https://sustainabledevelopment.un.org/?menu=1300>.

¹⁵² Waldman (2019).

¹⁵³ Steve Tombs, 'The Functions and Dysfunctions of Corporate Social Responsibility' in Grietje Baars (ed), *The Corporation* (Cambridge: CUP 2017); Paul K Shum and Sharon L Yam, 'Ethics and Law: Guiding the Invisible Hand to Correct Corporate Social Responsibility Externalities' (2011) 98 *Journal of Business Ethics* 549; James A. H. S. Hine and Lutz Preuss, "'Society Is out There, Organisation Is in Here": On the Perceptions of Corporate Social Responsibility Held by Different Managerial Groups' (2009) 88 *Journal of Business Ethics* 381.

¹⁵⁴ Michael S. Aßländer, 'Corporate Social Responsibility as Subsidiary Co-Responsibility: A Macroeconomic Perspective' (2011) 99 *Journal of Business Ethics* 115; Ronen Shamir, 'Socially Responsible Private Regulation: World-Culture or World-Capitalism?' (2011) 45 *Law and Society Review* 313.

¹⁵⁵ Krista Bondy, Jeremy Moon and Dirk Matten, 'An Institution of Corporate Social Responsibility (CSR) in Multi-National Corporations (MNCs): Form and Implications' (2012) 111 *Journal of Business Ethics* 281; but see Ulf Henning Richter, 'Drivers of Change: A Multiple-Case Study on the Process of Institutionalization of Corporate Responsibility Among Three Multinational Companies' (2011) 102 *Journal of Business Ethics* 261.

Such a notion demands that business strategy, governance and key aspects of corporate operations be interrogated within a responsibility framework,¹⁵⁶ so that ‘responsible’ actions or activities are not siloed or peripheral.¹⁵⁷ 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 power¹⁵⁸ and leadership¹⁵⁹ to transform socio-economic relations, exchanges and modalities in general.¹⁶⁰ Waldman¹⁶¹ 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.¹⁶²

Further, corporate use of ML is poised to bring about not only significant benefits but also great risks to social fabric, cohesion and trust.¹⁶³ The use of ML transforms work relations and human-machine interfaces,¹⁶⁴ resulting in new risks in relation to displacement, work configuration and mental and social well-being.¹⁶⁵ ML transforms business processes such as internal and external due diligence, the configuration of expert tasks and external accountability.¹⁶⁶ Corporations should place themselves firmly within the social fabric¹⁶⁷ 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

¹⁵⁶ Bonime-Blanc (2018).

¹⁵⁷ Vanessa M. Strike, Jijun Gao and Pratima Bansal, ‘Being Good While Being Bad: Social Responsibility and the International Diversification of US Firms’ (2006) 37 *Journal of International Business Studies* 850.

¹⁵⁸ John R Parkinson, *Corporate Power and Responsibility* (Oxford: Clarendon 1995).

¹⁵⁹ E.g. Julia M Puschunder, ‘Intergenerational Leadership: An Extension of Contemporary Corporate Social Responsibility (CSR) Models’ (2018) 2 *Corporate Governance and Organisational Behaviour* 7.

¹⁶⁰ See below.

¹⁶¹ (2019).

¹⁶² Kristijan Krkac, ‘Corporate Social Irresponsibility: Humans vs Artificial Intelligence’ (2019) 15 *Social Responsibility Journal* 786.

¹⁶³ Floridi et al (2018); Peter G Leonard, ‘Social Licence and Digital Trust In Data-Driven Applications and AI: A Problem Statement and Possible Solutions’ (2019) at <https://ssrn.com/abstract=3261228>.

¹⁶⁴ Such as in production and manufacturing, entailing physical, labour and human rights risks.

¹⁶⁵ Dimple Agarwal et al., ‘AI, Robotics, and Automation: Put Humans in the Loop’ (28 Mar 2018), https://www2.deloitte.com/insights/us/en/focus/human-capital-trends/2018/ai-robotics-intelligent-machines.html?id=us:2ps:3gl:confidence:eng:cons:111617:nonem:na:jlGgeatw:1100004742:268089541385:b:RLSA_Human_Capital_Trends:Automation_BMM:nb.

¹⁶⁶ Such as the use of ML in risk management that deals with internal and external accountability, Jeanne Boillet, ‘Why AI Is Both a Risk and a Way to Manage Risk’, (1 Apr 2018),

https://www.ey.com/en_gl/assurance/why-ai-is-both-a-risk-and-a-way-to-manage-risk.

¹⁶⁷ Siebecker (2020); Burghin and Hazan (2019).

context. The Guidelines arguably present a paradigmatic challenge to the traditional shareholder-centric focus of corporate theory and practice.¹⁶⁸

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. Black¹⁶⁹ 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 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 above. ML technologies tend towards decision-making and execution of actions that are relatively autonomous and opaque, and ML development and governance, such as in relation to their control and explicability¹⁷⁰ 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.¹⁷¹ The inherently interdisciplinary 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 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 only emerging. For example, the EU's General Data Protection Regulation provides for aspects of corporations' internal governance and risk management in relation to data,¹⁷² as well as redress mechanisms for affected data subjects.¹⁷³ Many issues remain outstanding as Section 2 has discussed, which are not

¹⁶⁸ Eleanore Hickman and Martin Petrin, 'Trustworthy AI and Corporate Governance – The EU's Ethics Guidelines for Trustworthy Artificial Intelligence from a Company Law Perspective' (2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3607225.

¹⁶⁹ Black (2001).

¹⁷⁰ One of the 6 principles developed by the AI4People group, Floridi et al (2018); Andrew D. Selbst & Julia Powles, 'Meaningful Information and the Right to Explanation' 7 Int'l Data Privacy L. 233 (2017).

¹⁷¹ Burghin and Hazan (2019); Floridi et al (2018) on the importance of inter-disciplinary development of AI governance.

¹⁷² Arts 35-39, EU GDPR on the institution of data impact assessment evaluations by companies and the role of the data protection officer; 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).

¹⁷³ Chapter 3, GDPR, especially Art 22 that provides for a right to challenge automated data profiling, see Jim Shook and Robyn Smith and Alex Antonio, 'Transparency and Fairness in Machine Learning Applications' (2018) 4 Tex A&M J Prop L 443; Margot E. Kaminski, 'The Right to Explanation, Explained' 34 Berkeley Tech. LJ 189 (2019).

clearly resolved in law or regulation. It also remains open whether specialist agencies should be set up as ML regulators.¹⁷⁴ 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 for access to justice and evidence by complainants.¹⁷⁵ 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,¹⁷⁶ ethical principles discussed above have tentatively filled the gap.¹⁷⁷ However there are a number of these bodies of principles and their influence is only 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.

4. 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.

Corporate Governance

First, we suggest that senior management and the Board 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 which can affect the financial bottom-lines and viability of companies.¹⁷⁸ However, in a broader manner, such 'risk management' matters are often not only matters of financial consequence but also matters of culture¹⁷⁹ which reflect a company's disposition, values and structures in decision-making. Culture matters for success and long-term viability¹⁸⁰ and at a broader level, successful companies often treat risk

¹⁷⁴ Shlomit Yanisky-Ravid and Sean K Hallisey, 'Equality and Privacy by Design: A New Model of Artificial Intelligence Data Transparency via Auditing, Certification, and Safe Harbor Regimes' (2019) 46 *Fordham Urb LJ* 428.

¹⁷⁵ European Commission (2019).

¹⁷⁶ Ryan Hagemann and Jennifer Huddleston Skees and Adam Thierer, 'Soft Law for Hard Problems: The Governance of Emerging Technologies in an Uncertain Future' (2018) 17 *Colo Tech LJ* 37.

¹⁷⁷ see n 111-114.

¹⁷⁸ Christoph Van der Elst and Marijn van Daelen, 'Risk Management in European and American Corporate Law' (April 2009) ECGI Law Working Paper No 122/2009, <http://ssrn.com/abstract=1399647>.

¹⁷⁹ Risk management as reflecting corporate cultures discussed in Anette Mikes, 'Risk Management and Calculative Cultures' (2007), <http://ssrn.Com/Abstract=1138636>; Annetta Cortez, *Winning at Risk* (Chicester: John Wiley & Sons, 2011) on a holistic definition of risk culture incorporating corporate organisational culture.

¹⁸⁰ 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* (NY: Jossey Bass Publishers, 2010); Joanne Martin,

management as an enterprise-wide phenomenon,¹⁸¹ 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 Board level is crucial for ML deployment. Suggestions include clarifying directors' duties for responsible deployment of ML,¹⁸² and the implications from the European Commission's Guidelines for AI.¹⁸³ Further, commentators propose that companies institute Board committees to oversee the deployment of innovative technologies,¹⁸⁴ and the appointment of Chief Innovation Officers¹⁸⁵ whose remit is not merely to develop technology, such as is the role of Chief Technology Officers in many companies,¹⁸⁶ but to oversee the development and deployment of new technologies in a responsible manner, working with compliance, ethics and responsibility departments.¹⁸⁷

Hickman and Petrin¹⁸⁸ however query 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 Boards¹⁸⁹ if not to assist Boards with information analysis.¹⁹⁰ 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 use of ML is misplaced. However, Chesterman rightly questions¹⁹¹ 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.¹⁹² Indeed, other scholars¹⁹³

Organisational Cultures: Mapping the Terrain (London: Sage, 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' (Harvard Business Review, Jan-Feb 2018), <https://hbr.org/2018/01/the-culture-factor>.

¹⁸¹ Brian W Nocco and René M Stultz, 'Enterprise Risk Management: Theory and Practice' (2006) 18 *Journal of Applied Corporate Finance* 8; Cortez (2011).

¹⁸² Siebecker (2020); Kieran Moynihan, 'What Will the Board of the Future Look like?' *Accountancy Ireland* (Dec 2018), 73.

¹⁸³ Hickman and Petrin (2020).

¹⁸⁴ Roger M Barker and Iris H-Y Chiu, 'From Value Protection to Value Creation- Rethinking Corporate Governance for Promoting Firm Innovation' (2018) *Fordham Journal of Corporate and Financial Law* 437.

¹⁸⁵ Timo Matthias Spitzer, 'The Importance of Human Leadership with Integrity in a Highly Regulated and Tech-Relevant Corporate Environment' (2020) 10 *Harv Bus L Rev Online* 1.

¹⁸⁶ 'The 4 different types of CTO - which one are you?' (12 Sep 2017) at <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.

¹⁸⁷ Bonime-Blanc (2018).

¹⁸⁸ (2020).

¹⁸⁹ Rob Wile, 'A Venture Capital Firm Just Named an Algorithm to its Board of Directors' (14 May 2014) at www.businessinsider.com.au/money-markets.

¹⁹⁰ Gary L Evans, 'Disruptive Technology and the Board: The Tip of the Iceberg' (2017) 3 *Economics and Business Review* 205. Ernst and Young, 'When Boards Look at AI- What Do They See?', https://www.ey.com/en_gl/board-matters.

¹⁹¹ Simon Chesterman, 'Artificial Intelligence and the Problem of Autonomy' (2020) *Notre Dame Journal on Emerging Technologies*, forthcoming.

¹⁹² Kuflik (1999); Balkin (2017).

¹⁹³ Iris H-Y Chiu and Ernest WK Lim, 'Technology vs Ideology: How Far will Artificial Intelligence and Distributed Ledger Technology Transform Corporate Governance and Business?' (2021) 18 *Berkeley Business Law Journal* forthcoming; Alan Dignam, 'Artificial Intelligence: The Very Human Dangers of Dysfunctional Design and

have articulated scepticism that substitutive changes of significant degree would occur at companies' corporate governance levels, due to institutional and moral reasons that restrain against such choices. At this juncture of choice, it is more imperative than ever for human leadership at Boardrooms to be explicit about the deployment of ML.

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 up different departments and relevant personnel, into internal and 'flat' 'networks' of governance, instead of leaving decisions regarding ML to siloed departments. Such internal organisation mirrors the wider external governance fabric.

Enterprise-wide frameworks¹⁹⁴ are already well-known for risk management.¹⁹⁵ 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 responsibility¹⁹⁶ 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.¹⁹⁷ Indeed enterprise-wide responsible innovation is arguably a regulatory benchmark in the financial sector. European guidelines¹⁹⁸ 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.¹⁹⁹ In this manner, instead of joined-up human leadership that oversees and reviews ML, even enterprise-wide systems can become technologically-reliant.²⁰⁰ We urge companies that intend to use and deploy ML in this manner to subject such decisions to the highest level of

Autocratic Corporate Governance' (Queen Mary University of London Working Paper 2019), <https://ssrn.com/abstract=3382342>; Luca Enriques and Dirk Zetzsche, 'Corporate Technologies and the Tech Nirvana Fallacy' (2019) at http://ssrn.com/abstract_id=3392321, (2020) *Hastings Law Journal*, forthcoming.

¹⁹⁴ Thomas H Stanton, *Why Some Firms Thrive While Others Fail: Governance and Management Lessons from the Crisis* (Oxford: OUP 2012), chs 3, 5 on the importance of enterprise-wide frameworks including risk management

¹⁹⁵ See n79.

¹⁹⁶ Cortez (2011).

¹⁹⁷ 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 Study' (2014) 1 *Journal of Responsible Innovation* 9.

¹⁹⁸ European Banking Authority, 'Guidelines on Internal Governance under Directive 2013/36/EU' (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](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), ch 18, pp45-46.

¹⁹⁹ Eg Bryan Buck and John Morrow, 'AI, Performance Management and Engagement: Keeping Your Best Their Best' (2018) 17 *Strategic HR Review* 261.

²⁰⁰ Kenneth A Bamberger, "Technologies of Compliance: Risk and Regulation in a Digital Age" (2009/10) 88 *Texas Law Review* 669.

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.²⁰¹

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 their feedback when developing internal frameworks for risk management and responsibility.²⁰² Such external engagement and discourse should be navigated within the thick and broad paradigm of corporate responsibility, seeking multi-stakeholder input and co-governance.²⁰³ These external initiatives should not be instrumental and cosmetic forms of communication or 'washing'. There should be procedural and also substantive implications of such engagement and discourse.

Stakeholders and Gatekeepers

Stakeholder engagement should include meaningful two-way communications such as dialogue and feedback from those that would be affected by the use and deployment of ML.²⁰⁴ An initial circle of directly affected constituents comprises an internal and external aspect. The internal aspect relates to employees and other workers, and the external aspect relates to constituents such as suppliers and customers, and perhaps regulators.²⁰⁵ There should be proactive engagement²⁰⁶ 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.²⁰⁷ Companies should be willing to treat their stakeholders, 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

²⁰¹ Johnson (2015).

²⁰² Sonia K Katyal, 'Private Accountability in the Age of Artificial Intelligence' (2019) 66 UCLA L Rev 54.

²⁰³ Ruth V. Aguilera, Deborah E. Rupp, Cynthia A. Williams and Jyoti Ganapathi, 'Putting the S Back in Corporate Social Responsibility: A Multilevel Theory of Social Change in Organizations' (2007) 32 The Academy of Management Review 836; Jan Lepoutre, Nikolay A. Dentchev and Aimé Heene, 'Dealing with Uncertainties When Governing CSR Policies' (2007) 73 Journal of Business Ethics 391.

²⁰⁴ Leonard (2019).

²⁰⁵ A perspective offered in Mirka Snyder Caron, 'The Transformative Effect of AI on the Banking Industry' (2018) 34 Banking and Finance Law Review 169.

²⁰⁶ Burghin and Hazan (2019).

²⁰⁷ Jennifer S Fan, 'Employees as Regulators: The New Private Ordering in High Technology Companies' (2019) 5 Utah Law Review 973.

and whether stakeholders and communities could catch up with their implications;²⁰⁸ choices to be made in relation to human agency or oversight and standards of such oversight;²⁰⁹ the extent of human accountability in spite of the black box nature of ML.²¹⁰ These substantive choices reflect principles in relation to accountability²¹¹ and justice,²¹² as well as values embodied in institutions and society,²¹³ and should be made by companies within a thick and broad paradigm of social responsibility.²¹⁴

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 longer-tailed and unexpected reputational and social risks, and affect corporations in terms of their social legitimacy.

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 is not understood in a sense that promotes risk aversion and avoidance of innovation but as being appreciative of 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.²¹⁵ 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.²¹⁶ Regulators may also wish to consider instituting ML sandboxes²¹⁷ for corporations so that use and test can be carried out within supervised parameters that aim at minimising stakeholder and external harm. The sandbox concept has been pioneered in relation to the fintech industry,²¹⁸ and it provides a

²⁰⁸ Wallach (2015).

²⁰⁹ Chesterman (2020); Kuflik (1999); Balkin (2017).

²¹⁰ Martin (2019).

²¹¹ Ibid.

²¹² Liu (2017); Floridi et al (2018).

²¹³ European Commission (2019).

²¹⁴ Krkac (2019); Burghin and Hazan (2019).

²¹⁵ Steve Clarke, 'Future Technologies, Dystopic Futures and the Precautionary Principle' (2005) 7 Ethics and Information Technology 121.

²¹⁶ 'Self-driving cars to test city limits' (Scientific American, 5 Nov 2019), <https://www.scientificamerican.com/custom-media/pictet/self-driving-cars-to-test-city-limits/>; designated test zones and roads for self-driving cars e.g in Korea and Beijing.

²¹⁷ Hagemann et al (2018); Bertolini (2016).

²¹⁸ Financial Conduct Authority, *Regulatory Sandbox* (Nov 2015); *Default Standards for Sandbox Testing Parameters*, <https://www.fca.org.uk/publication/policy/default-standards-for-sandbox-testing-parameters.pdf>; *Regulatory Sandbox Lessons Learnt Report* (2017),

useful regulatory tool for the public and private sectors to engage in co-learning and shaping responsible and socially accountable innovation. However, improvements²¹⁹ can be made to the sandbox concept, such as involving multi-stakeholder governance²²⁰ and increasing transparency with regard to the results of sandbox experiments and lessons for corporate strategy and regulatory reform.²²¹

Prudential Provision

Further, corporations intending to deploy ML should consider making ‘prudential’ provision in relation to the risks discussed in Section 2. Even if the laws and regulations are not determinate in respect of liability,²²² corporations could consider compensatory obligations as a matter of social goodwill in relation to the adverse impacts on the stakeholders and communities.²²³ 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 al²²⁴ 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 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.²²⁵

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.²²⁶ On the

<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 W Arner, Robin Veidt and Dirk A Zetsche, ‘Building FinTech Ecosystems: Regulatory Sandboxes, Innovation Hubs and Beyond’ (2019) at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3455872.

²¹⁹ Such as clarity for sandboxed firms’ rights and obligations, and competition issues at industry level, discussed in Hilary J Allen, ‘Regulatory Sandboxes’ (2019) 87 *George Washington Law Review* chk; Brian Knight and Trace Mitchell, ‘The Sandbox Paradox: Balancing the Need to Facilitate Innovation with the Risk of Regulatory Privilege’ (2020) *South Carolina Law Review* forthcoming, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3561860.

²²⁰ Dirk A Zetsche, Ross P Buckley, Douglas W Arner and Janos N Barberis, ‘Regulating a Revolution: From Regulatory Sandboxes to Smart Regulation’ (2017) 23 *Fordham Journal of Corporate and Financial Law* 31.

²²¹ Iris H-Y Chiu, ‘A Rational Regulatory Strategy for Governing Financial Innovation’ (2017) 8 *European Journal of Risk Regulation* 743.

²²² Section 2.

²²³ European Commission (2019); Peter M Asaro, ‘The Liability Problem for Autonomous Artificial Agents’ (2016) *Conference paper for Association for the Advancement of Artificial Intelligence* 190.

²²⁴ (2018).

²²⁵ Vladeck (2014).

²²⁶ Sylvia Lu, ‘Algorithmic Opacity, Private Accountability, and Corporate Social Disclosure in the Age of Artificial intelligence’ 23(1) *Vanderbilt Journal of Entertainment & Technology Law* (forthcoming 2021), <https://ssrn.com/abstract=3582222>.

one hand, such disclosure reform may focus companies on making material disclosure with a financial bent,²²⁷ but on the other hand, the expansion of social disclosure in securities disclosure²²⁸ can lead to changes in companies' orientation and culture in treating accountability.²²⁹ There is certainly scope for explicit adoption of mandatory disclosure such as in non-financial disclosure in the UK²³⁰ and EU²³¹ 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.²³²

It is arguable that voluntary corporate responsibility reporting standards such as the GRI standards²³³ 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 relation to 'Management Approach'.²³⁴ 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 disclosed²³⁵ and ML deployment can be relevant for disclosure in relation to the training and education of employees.²³⁶ Further, disclosure should be made in relation to customer privacy and data safety.²³⁷ 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.²³⁸

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.²³⁹ The impact on suppliers,²⁴⁰ customers,²⁴¹ job security for employees²⁴² can also be more clearly articulated. Corporations' stance on innovation and the pace of adoption of ML can also be made accountable under economic

²²⁷ The financially driven nature of securities disclosure, see Iris H-Y Chiu, 'The Paradigms for Mandatory Non-Financial Disclosure: A Conceptual Analysis- Parts 1 and 2' (2006) *Company Lawyer* 259, 291.

²²⁸ Barnali Choudhury, 'Social Disclosure' (2016) 13 *Berkeley Business Law Journal* 183.

²²⁹ 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?' (2017) 5 *European Company Law* 193; but see doubts in Andrew Johnston, 'Market-Led Sustainability through Information Disclosure' in Christopher Bruner and Beate Sjafell (eds), *Cambridge Handbook of Corporate Law, Corporate Governance and Sustainability* (Cambridge: CUP, 2019), ch15.

²³⁰ S414CA, Companies Act 2006.

²³¹ Art 19a, 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.

²³² Leonard (2019).

²³³ <https://www.globalreporting.org/Pages/default.aspx>.

²³⁴ GRI Reporting Standard 103.

²³⁵ GRI Reporting Standard 403.

²³⁶ GRI Reporting Standard 404.

²³⁷ GRI Reporting Standard 418.

²³⁸ GRI Reporting Standard 413.

²³⁹ Such as in GRI Reporting Standard 103.

²⁴⁰ GRI Reporting Standard 414.

²⁴¹ GRI Reporting Standard 416, 418.

²⁴² Perhaps under GRI Reporting Standard 401.

disclosures²⁴³ 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.²⁴⁴

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 risks;
- b institute enterprise-wide structures for broad and integrated governance of ML risks 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 risks;
- d to engage in multi-stakeholder governance frameworks integrating the public and private dimensions, in order to participate in the shaping of public policies;
- e to make voluntary disclosure of ML risks and management even if 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.

5. 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 the cognizance for the need to manage the risks of deploying ML systems seems slower to catch on. 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

²⁴³ GRI Reporting Standard 201.

²⁴⁴ GRI Reporting Standard 417.

approaches, prudential provision, broad accountability mechanisms and a networked multi-stakeholder approach to shaping and governing their strategic deployment of ML technologies.