Center for Research in Economics, Management and the Arts

Artificial Intelligence and Big Data in Sustainable Entrepreneurship

Working Paper No. 2021-11

CREMA Südstrasse 11 CH - 8008 Zürich www.crema-research.ch

Artificial Intelligence and Big Data in Sustainable Entrepreneurship

Steve J. Bickley[a,b], Alison Macintyre[b], and Benno Torgler[a,b,c]

[a] School of Economics and Finance, Queensland University of Technology, 2 George St, Brisbane QLD 4000, Australia
[b] Centre for Behavioural Economics, Society and Technology (BEST), 2 George St, Brisbane QLD 4000, Australia
[c] CREMA – Centre for Research in Economics, Management, and the Arts, Südstrasse 11, CH-8008 Zürich, Switzerland

Abstract:

The recent acceleration and ongoing development in Artificial Intelligence (AI) and its related (and/or enabling) digital technologies presents new challenges and considerable opportunity on which businesses and individuals may capitalise. In the era of BD – and with increasing societal value being placed on sustainable business to minimise or mitigate the impacts of climate change – customers and regulators alike are turning to organizations to tackle large and complex sustainable development goals. AI and BD can help interpret and monitor the environment, identify which problems need attention, design strategies, generate decisions, and action the tactics. A key challenge in sustainable entrepreneurship is a failure to integrate 'systems thinking' beyond a limited number of issues, rather than taking the time to understand the relationship between business processes, macro ecological processes, boundary conditions, and tipping points. The recent and substantial increase in data availability simultaneously advances the potential for AI and BD to enhance ecological sustainability through validation and testing of beliefs and hunches, offering empirical guidance to every stage involved in decision making, and comparing inputs against the outcomes – particularly in fast-changing and highly uncertain environments. To prepare, we must strategize by looking to and engaging with the market, our clients, and our customers for guidance. Only then can we then proceed to develop viable and sustainable business models and plans. To reap the rewards of progress in AI, BD, and related technologies, we need to find ways to race with the emerging technologies while also identifying ways to act in symbiosis with them. The demands of adapting to AI and BD are no different from the situation with past disruptive technologies such as the automobile, radio, and the Internet.

Keywords: Artificial Intelligence, Big Data, Entrepreneurship, Sustainability, Expert Systems

The definition of man's uniqueness has always formed the kernel of his cosmological and ethical systems. With Copernicus and Galileo, he ceased to be the species located at the center of the universe, attended by sun and stars. With Darwin, he ceased to be the species created and specially endowed by God with soul and reason. With Freud, he ceased to be the species whose behavior was – potentially – governable by rational mind. As we begin to produce mechanisms that think and learn, he has ceased to be the species uniquely capable of complex, intelligent manipulation of his environment.

Herbert Simon (1977), The New Science of Management Decision, p. 37

1. Introduction

The recent acceleration and ongoing development in Artificial Intelligence (AI) and its related (and/or enabling) digital technologies (e.g., computing hardware, cloud computing, Internet of Things (IOT), and quantum computing) presents new challenges and considerable opportunity on which businesses and individuals may capitalise. AI and related Information Technologies (IT) are poised to increase productivity, lower costs (capital and operational), reduce human error (Akerkar, 2019), and pre-empt, limit, and prevent exposure to hazardous situations. Such advances will contribute to the pursuit of organizational intelligence, assisting with the process of information provision and interpretation, and therefore in formulations of organizational aspirations (e.g., goals, visions, and plans). Information allows us to understand whether policy shifts are required, to monitor and assess the structure and dynamics of the company, industry, and environment, to determine how well the company is doing, and to understand the present state of the system, *all* in order to plan and prepare for the future (Simon, 1977, p. 125). Top management relies heavily on external environmental information to better understand how the company survives effectively (Simon, 1977). AI and BD can help interpret and monitor the environment, identify which problems need attention, design strategies, generate decisions, and action the tactics. As Allen Newell (1990) has stressed, "AI is the study of the mechanisms of intelligence and all supporting technologies" (p. 40). Herbert Simon (1995) calls it "complex information processing" (p. 939). Managers and other business leaders (e.g., CEOs, board members, team leaders) would do well to keep up, because "over the next decade, AI won't replace managers, but managers who use AI will replace those who don't" (Brynjolfsson and McAfee, 2017, p.20). As AI allows organizations to complete some administrative tasks faster, better, and at lower costs than human managers, it will require managers to reposition themselves and adapt if they are to survive and thrive in this new AI-enabled environment (Kolbjørnsrud, Amico and Thomas, 2016).

Human judgement requires the combination of experience and expertise. But as March (2010) discusses, experience is often ambiguous, which challenges the inferences to be drawn from it and confounds learning. Such complications are affected by biased information-processing habits such as biases towards conserving beliefs, simple causalities, or historical certainty (p. 13). Intelligent actions means effective problem solving that deals with complex interactions in a dynamic world; it is to this end that the use of AI-enabled systems in organisations is expanding (Duan, Edwards, and Dwivedi, 2019). By learning, analysing, recombining, and constantly updating known situations and symptoms within a given context, AI has the potential to replace contingent decision making by humans in organisations with known responses and remedies. Management scholars have explored aspects such as the role of prediction as an input into decision-making, as a tool to generate high returns on investment, and a way to understand the implications for business strategy (Agrawal, Gans, and Goldfarb, 2018). However, less emphasis has been given to how AI can help companies and managers plan, measure, site, forecast, innovate, or develop products and services in an environmentally sustainable way. As noted by Bocken et. al. (2014, p.42): "[b]usiness as usual is not an option for a sustainable future". Schaltegger (2018) stresses that the complexity, wickedness, interconnectedness, and uncertainty of sustainability phenomena allows no "room for complacency and ignorance on the corporate level" (p. 22). At the same time, the urgency of the current situation requires urgent innovation, as "[t]he amount and quality of remaining resources are decreasing due to the large consumption worldwide" (Strandhagen et. al. 2017, p. 359); yet, the processes or priorities involved in the necessary transition are still disputed.

Managerial attention on AI and Big Data (BD) – in combination with environmental responsiveness – can affect managers' expectations regarding available opportunities. Reflecting on the evolution of operations management, Graves (2021) points out several future research opportunities arising from the questions of how we can use AI to enhance approaches to the design, planning, and improvement of an operating process – and what new operations management issues emerge as a result of using AI applications across those processes (p. 6). AI systems may increase the very capabilities for change crucial to establishing an organizational culture that promotes sustainability (Eccles et al., 2012), and related personal, process, and environmental hazard management (Garvin and Kimbleton, 2021). This is a potential multiplier of adaptation, because operations management challenges can affect the survival of companies who try to innovate with respect to production and delivery of goods and services that are environmentally sustainable (Plambeck, 2013), and in fast-changing and highly uncertain environment, an experimental and iterative approach to projects (e.g., greenfield, upgrades, process optimisation, and repairs) in operations may be best (Pich et al., 2002).

On the other hand, evidence indicates that high performance in sustainability and corporate social responsibility is good for business; highly sustainable companies significantly outperform their less sustainable counterparts over the long term, both in terms of stock market and accounting performance – perhaps owing to their well-developed processes for stakeholder engagement, long-term orientation/mindset, and high retention of long-term investors (Eccles et al., 2014). As investors increasingly "seek to align their portfolios with their values" (Cort and Esty 2020, p. 492), there is growing pressure for ESG investment scorecards to go beyond the 'greenwashing' that may have been previously accepted, moving organisations further towards stakeholder capitalism (Tucker and Jones, 2020). While the neoclassical model of the firm is already being transformed (Stubbs and Cocklin, 2008) from a perspective in which the "primary obligation of corporations is to maximize profits for shareholders" (p. 103), there are still areas of inertia in the process of moving towards "stakeholder capitalism", or businesses models based in stakeholder theory (Schaltegger, Hörisch and Freeman, 2019). Attempts to bring all stakeholders' interests into the decision-making calculations will require more synthesising ability than humans can currently manage alone. Hörisch, Schaltegger, and Freeman (2020) propose a model that integrates stakeholder theory and sustainability accounting, enabling firms to incorporate many forms of information from stakeholder engagement efforts that are particularly useful for the firm. This integrated model takes into account both ethical and business issues, rather than separating them out; it considers value creation beyond financial or monetary concerns, while also including those forms of value; and generates accounting information that is useful or valuable to stakeholders. AI and BD enabled technologies have the capacity to bring such a theoretical model to life, allowing empirical testing of these different value flows within the system.

Future developments might see more recognised and verifiable ways to track sustainability performance, with industry-verified marks of approval, or stop-light (green, yellow, red) indicators of sustainability for everything from investment portfolios to packaged goods. While global environmental standards do not seem to produce the kind of liability that negatively affects market value for multi-national enterprises (Dowell, Hart, and Yeung, 2000), organizations subject to higher regulatory surveillance are more likely to follow through on their commitments to sustainable self-regulation (Short and Toffel, 2010). An openness to transparency with respect to sustainability represents a recent change for many businesses. Almost thirteen years ago, Stubbs and Cocklin (2008) noted that businesses were only likely to "go green" if it was good for the business, or if they experienced outside pressure; for example, if they were subject to stakeholder demands, or wanted to retain or regain their social licence to operate. Organizations which become targets for activism (typically a high reputability corporation) can also find themselves stuck in a cycle of reputational damage and subsequent repair, with increasing focus placed on corporate sustainable responsibility to make up for previous wrong doings and mishaps (King and McDonnell, 2012).

Proactive environmental strategies have also been linked to the development of proficiencies in stakeholder integration, higher-order learning, and continuous innovation / organizational learning (Sharma and Vredenburg, 1998), all important traits when competing in an increasingly complex and uncertain environment. Competitive advantages can also be generated in emerging capabilities of intentional, natural-resource-based strategic management (Hart, 1995). Ten years ago, a survey of 2,874 managers and executives from 113 countries indicated that up to two-thirds of respondents believed sustainability was of critical importance for an organisation to be competitive (Kiron et al., 2011). The recent and substantial increase in data availability simultaneously advances the potential for AI and BD to enhance ecological sustainability through validation and testing of beliefs and hunches, offering empirical guidance to every stage involved in decision making and comparing inputs against the outcomes. Thus, this contribution explores the implication of AI and BD on sustainable entrepreneurship practices, procedures, decision-making processes, and monitoring/analysis. While AI can help entrepreneurs to scale (Obschonka and Audretsch, 2019), it also offers the potential to accurately understand how to sustainably increase those capabilities. Likewise, there are opportunities and risks with achieving "sustainable identifiability". In this contribution we aim to shed light on the three following questions:

1) How can AI and BD drive progress in sustainable entrepreneurship?
2) What are the major challenges that must be overcome, and opportunities available to seize?
3) What can sustainable organizations and entrepreneurs do to prepare, position, and find competitive advantage in an AI and BD future?

In the following sections, we will first discuss AI and BD analytics in the context of entrepreneurship, and sustainable entrepreneurship. Later, we identify some major challenges that must yet be overcome, and opportunities available to seize. We then summarise our findings, returning to the above research questions and suggesting future directions for both AI and management science research and practice to direct their efforts towards potentially fruitful applications of AI and BD in sustainable entrepreneurship.

2. AI and BD in Entrepreneurship

Artificial intelligence can be broadly described as "the examination of how digital computers and algorithms perform tasks and solve complex problems that would normally require (or exceed) human intelligence, reasoning, and prediction power needed to adapt to changing circumstances" (Obschonka and Audretsch, 2020, p. 530). This is relevant for organisations, as they often struggle to deal with significant systematic changes because established firms can be a reflection of the structure of their environment, having invested years of learning and fine-tuning within their existing system (Henderson and Serafeim, 2020). Nevertheless, the definition, scope, and focus of AI research and innovation has changed over time (Kok et al., 2009). Russell and Norvig (2010) identify and cluster the four main approaches to AI as follows: *thinking humanely*, *thinking rationally*, *acting humanely*, and *acting rationally*. For the most part, the "rational" agent or *acting rationally* approach has dominated AI research owing to its generality, scalability, mathematical foundations, and ready application to real world problems. In particular, AI sub-domains such as machine learning (ML) and deep learning (DL) – iterative methods of learning based on probability theory and statistics – have helped humans achieve great engineering feats, even under circumstances where there are still considerable uncertainties in current states, observations, and future predictions. AI allows for the use of complex models that assist in the decision-making process by not only including the firm itself, but also the economic environment, and therefore are suitable for use in strategy formulation and planning.

The key advantage of artificial – in contrast to human – intelligence is its scalability, longevity, and ability to continuously learn/adapt to a changing environment. In doing so, AI can increase productivity, lower costs (capital and operational), and reduce human error (Akerkar, 2019) by identifying, tracking, and acting on trends, seasonal effects and movements in the data and adapting responses based on feedback mechanisms and incentive functions. As Yadav et al. (2007) point out, CEO attention (i.e., choice of what to focus on) is a critical driver of innovation and organizational direction, even when outcomes are planned far into the future, and new products, services, and processes are both distinct and novel. A CEO empowered by AI and BD is able to let curiosity and data guide the search for new risks and opportunities, freeing up the CEO's attention for making decisions that formulate 'big picture' strategies and organizational direction. After all, tackling climate change requires concerted and authentic efforts of the top management in setting organizational direction, and driving sustainable progress (Henderson and Serafeim, 2020). The ability to perceive, respond, and adapt business plans, processes, and procedures is critical for survival in increasingly complex, competitive, and uncertain times. To do this, organizations (young and mature alike) should position themselves strategically in the market by leveraging historically derived portfolios of assets and resources (Lockett et al., 2009), a concept otherwise known as the resource-based view of the firm. Organizational knowledge is one such strategic asset used by companies to achieve competitive advantage (Bollinger and Smith, 2001). This knowledge exists in many places and forms; it can be structured, semi-structured, and unstructured; and also exists in human minds (Hlupic et al., 2002). Organizations store their knowledge in procedures, norms, rules, and forms – and humans in organizations are socialized into these organizational beliefs (March, 1991), which affects the level of adaptability and learning. Effective selection of forms, routines, or practices is crucial to organizational survival (March, 1991). Accordingly, effective knowledge management can help organizations perceive and respond to strengths, weaknesses, opportunities and threats; act, assess, and adapt through continuous improvement; generate real-time[1] response and monitoring capabilities; and create and understand information that is of real value to clients' and customers' needs (Hlupic et al., 2002). As Charles (2009, p. 807) suggests: "The next big force for behavioral change may be technology that brings consumers face-to-face with their energy consumption"; not only as they understand the real effect of their actions and behaviours on the environment, but also because it compares the user's consumption with others in their area or peer group. This could also be implemented in knowledge systems via smart meters and continuous feedback for entrepreneurs making minute-by-minute decisions on their bottom line in ethical and sustainable supply chain management. For example, Strandhagen et. al. (2017) describe the potential of this capacity for

[1] Using a large-scale field experiment to understand the overcoming of salience bias, Tiefenbeck et al. (2018) find that real-time feedback on resource consumption of daily, energy-intensive activity (showering) substantially reduces resource consumption.

insights and real time information as Logistics 4.0, laying out how it could spur “new business models”.

Going one step further, we can consider a future where complex knowledge systems are combined with expert systems “to make available some of the skills of an expert to non-experts” (Siler, 2005, p. xiii). In this way, we can preserve shared knowledge and foster organizational learning and progress; however, there can be a trade-off between the benefits derived from (i.e., the usefulness) of a system’s recommendations and the cost of maintenance (fixed and/or variable) (Bensoussan et al., 2009), particularly if system learning and adaptation is less than effective. High levels of uncertainty regarding the nature of the organization’s environment or the rates of environmental change requires enhanced learning and experimentation. For example, rapid changes put a premium on knowledge, the creation of knowledge, and learning (Sitkin, Sutcliffe, and Schroeder, 1994), and increased knowledge improves the reliability of performance by reducing performance variability (March, 1991). Expert systems and predictive analytics have become affordable and provide ways of integrating otherwise unmanageable amounts of data when evaluating alternative decision options (Jarrahi, 2018). Adaptive processes tend to refine exploitation more rapidly than exploration – which might be effective in the short run – but self-destructive in the long-run, trapping a firm in suboptimal stable equilibria due to positive local feedback that also produces strong path dependency (March, 1991). Adaptive processes can be seen as methods of sequential sampling; i.e., alternatives that have experienced relatively good outcomes in the past are more likely to be sampled than other alternatives, which can lead biases in the process. For example, errors will not be corrected where they involve alternatives that initially appeared worse than they actually are, which leads to bias against new and risky alternatives (Denrell and March, 2001).

In contrast to “hard” computing methods, soft computing methods do not promise correct or optimal solutions, but are often useful in situations where hard methods are unable to compute solutions in a robust, reasonable, or timely manner. This is particularly the case in situations requiring tolerance and even exploitation of imprecision, uncertainty, and partial truths (Ibrahim, 2016), and where complex interdependencies, feedback loops, and emergent phenomena are commonplace; for example, in many human systems exhibiting complex behaviours such as non-linearity, sharp discontinuities, and highly unpredictable collective phenomenon/properties that are not attributable solely to the aggregate sum of individual agent behaviours (Holling, 2001). AI, BD, and associated enabling technologies appear well suited to such problems, especially those that take a "softer" approach to AI. Such soft AI methods perform many practical operations such as classification, clustering, and optimisation and have successfully been applied to the task of making sense of structured and unstructured data from mixed and varied sources alike by "exploiting the imprecision and uncertainty in decision making processes" (Ibrahim, 2016, p. 35). Probabilistic approaches have proven useful in the past (Matzkevich & Abramson, 1995), particularly when problem environments are highly complex, unstructured, and ill-defined. For example, Orriols-Puig et al. (2013) present and implement a novel AI which incorporates fuzzy logic and genetic algorithms and operates in an unsupervised manner in the discovery of interesting association rules from largescale (BD) databases, and apply this to a problem of distribution channel optimisation. A key characteristic of their system is the ability to automatically generate new insights directly from data; especially useful in discovering trends and patterns that may have been previously overlooked by human experts due to their various biases and bounded abilities to perceive, process, respond, and adapt to new information. Quantum concepts promise further advances in their ability to handle vague and ill-defined queries of large, complex datasets and knowledge structures (Bickley et al., 2020), which is especially important in the era of BD and IOT. While typically resource heavy, quantum computing and hence access to its abilities is expected to become less expensive over time with distributed and decentralised (therefore, flexible and resilient) interconnected quantum computational networks (Kimble, 2008) offering a potential solution.

Analogous transfer learning of theory, concepts, and methods used in AI and BD analytics (e.g., design principles used in the development of genetic algorithms as suggested by Zhang and Van Burg 2019) can also help to enrich the practice of entrepreneurship in the hopes of achieving a more robust and design-focused science. Likewise, the unpredictable and persistent/persevering behaviours and decision-making of entrepreneurs – and the literature and management practices which have sought to understand them – have plenty to offer in developing more creative, insightful, and lasting impacts of AI by focusing on the goals and objectives of sustainable entrepreneurs. Such cross-fertilization of concepts can breathe new life into otherwise slow moving, exhausted, or otherwise mature (perhaps dead or dying) research programmes.

AI- and BD-enabled approaches to the analysis of large scale, 'open' social media datasets. Sheng et al. (2020), e.g., describe three main uses for BD analytics in the business management literatures: descriptive/diagnostic analyses (i.e., what potential patterns and trends are embedded in historical data that provide insights into cause-and-effect relationships and how can these be used to improve existing operations?), prediction (i.e., what event/behaviour is most likely to happen in the future based on current and historical facts?), and prescription (i.e., what should we do and why?). For example, data generated from Twitter, Facebook, and LinkedIn have been used to explore the regionality of personality and its impact on entrepreneurial activities (Obschonka et al., 2020), a descriptive endeavour used to partially map regional entrepreneurship. BD has also been used to investigate the relationship between news coverage of entrepreneurship and regional entrepreneurial activity (von Bloh et al., 2019); and in a similar vein, it could be used to shed light on many other important policy questions (e.g., mismatches between actual reporting of entrepreneurial news and news perception) and inform prescriptive policymaking on how best to support innovation and entrepreneurship through media coverage and societal spotlighting. This is of particular interest to those concerned with the characterisation and development of entrepreneurial regions and ecosystems and understanding the processes and networks through which they derive entrepreneurial outcomes. The continued collection, analysis, and dissemination of large-scale BD datasets from varied sources (e.g., GIS, open government, pollution monitoring stations, boat/plane/car tracking systems, and sources of personal mobility) and across different spatio-temporal scales will provide further innovation on the study of dynamic and complex human systems and organizations/institutions. AI is one approach which, for the most part, seems up to the challenge of integrating and deriving new knowledge from such large, complex, and heterogenous BD sources.

3. Sustainable Entrepreneurship

The freedom to pursue social and economic development depends on societies' ability to act within a safe distance of the planetary boundaries that provide life-support properties of environmental and human wellbeing (Rockström et al., 2009). The planetary boundary (PB) framework offers insights into the risk of human perturbations and helps to identify levels of anthropogenic perturbations below the risk of destabilization. Sustainable entrepreneurship follows from the premise that entrepreneurial activities performed in the pursuit of opportunities should not degrade or act in detriment to the environments (social, economic, and environmental) in which they operate and preferably, contribute to the betterment of society, nature, and other sustainable development goals (SDGs) (Muñoz & Cohen, 2018). A natural-resource-based view of firms relies on three strategic capabilities: pollution prevention, stewardship, and sustainable development (Hart, 1995). In a follow up paper, Hart and Dowell (2011) emphasized that most of the previous work had focused on whether or not it pays to be green, concentrating on elements such as profit and pollution control, stock market reaction to disclosure of environmental liabilities, or how voluntary disclosure of environmental practices affect market valuation. According to Hart and Dowell (2011), progress was achieved in identifying broad capabilities and resources that allow the pursuit of financial and environmental success (p. 1467); however, empirical work on product stewardship and sustainability are still underdeveloped nascent areas.

As product stewardship efforts require coordination across a number of domains and entire value chains or life cycle of a firm's product system (Hart and Dowell, 2011), analytical tools in AI and BD can contribute to the required integration capabilities, allowing simulation of how simple changes may affect firm performance; for example, by reducing potential uncertainties due to various interdependencies in the decision making process and the development of successful product stewardship strategies. This can assist in the programmed decision-making process. As Kleindorfer, Singhal and Van Wassenhove (2005) stress, integrating decisions over the life cycle of products is essential to continued survival, but such dynamic optimization is challenging and depends on designing products and processes that allow performance tracking. AI and BD systems allow simulation of sustainable development strategies before scaling them up for real world trials and implementation. Thus, AI and BD systems can help companies to be agile and adaptive when balancing people needs and demands with environmental objectives and planetary needs. We can, as Simon (1977) points out, design into a complex and changing environment with adaptive mechanisms that allow us to respond in a flexible manner to the demands the environment places upon us while homeostatic control over the environment within the firm is more localized (p. 25). We are in a technological revolution of the decision-making process; yet, despite various interdisciplinary approaches, there is still no model to "solve or avoid environmental or social issues, whilst aiming for economic benefits" (Pieroni, McAloone, and Pigosso, 2019, p. 199).

AI and BD can support operations management, helping companies to embrace sustainability in (re)formatting their objective functions and the constraints they face in their (global) production-distribution models (Kleindorfer et al. 2005, p. 490). Current modelling efforts rely heavily on a deterministic knowledge approach, disregarding informational frictions and complexities faced in the real world (Anand and Giraud-Carrier, 2020); while managerial problems can be classified by how well they are structured or programmed. In shifting away from reliance on a purely deterministic approach, there are real advantages in being able to combine operational research or management science with AI systems that can rely more on heuristic programming to deal with less structured, ill-structured, or unprogrammed decisions. As AI systems are moving towards the ability to program themselves, new challenges will emerge in the mediation of compiling systems. In such a setting, AI and BD can be used as a tool to substantially increase the problem-solving capabilities of humans in non-programmed situations that usually rely heavily upon human judgement, insights, and intuition, and applying a long-term lifecycle and sustainability perspective. The current core challenge is not the generation, storage, or dissemination of information, but rather the filtering and compressing of it to deal with the high information processing demands, and then distributing it selectively and effectively within the organisation. As Simon (1987) has pointed out:

> [i]t is a fallacy to contrast 'analytic' and 'intuitive' styles of management. Intuition and judgement – at least good judgment – are simply analyses frozen into habit and into the capacity for rapid response through recognition. Every manager needs to be able to analyze problems systematically (and with the aid of the modern arsenal of analytical tools provided by management science and operations research) (p. 63).

Planning and decision-making in complex organisations is affected by core limitations of information processing systems; for example, limited knowledge of the laws that govern the systems being planned, the level of clarity in discovering representations that handle salient situational and contextual factors in the mass of details, the availability of powerful heuristic search methods, and the availability of relevant real-world data (Simon 1977, p. 109). As Freiberg et al. (2020) stress, "for corporate managers, the main challenge is to understand how different environmental impacts can be measured, compared, and integrated into the decision-making process to allow for better, more seamless management of risk, return, and impact, as well as more efficient, sustainable allocation of resources" (p. 2). Various tools are available such as Environmental Accounting to help companies in contributing to sustainable development and environmentally beneficial decision-making (Schaltegger, 2018). The connection to accounting statements can lead to actionable signals (Serafeim, Zochowski, and Downing, 2019). The goal of impact-weighted accounts is to translate social and environmental impact into comparable units in a meaningful way, such that business managers and investors are able to understand and visualise the information and implement existing financial business analysis tools (Serafeim, Zochowski, and Downing, 2019). Connecting tools like this into BD datasets of global stock and flow monitoring of planetary boundary measures – for example, net natural resources, pollution, or political and social instability – could be used in combination with AI to monitor and forecast in real time. Such AI and BD-informed networks could warn of upcoming problems that require course correction, or with enough information and knowledge input to the decision-making process, could autonomously those plot course corrections and implement solutions. Ongoing iterations of PESTEL (Political, Economic, Social, Technological, Environmental/Ecological, Legal[2]) or SWOT (Strengths Weaknesses, Opportunities, and Threats[3]) analyses, constantly updated with new AI- and BD-informed insights into operational and climate/environmental data gathered globally could be used to devise, analyse, and revise business models and strategy through data-driven exploration.

Recognising that small adjustments at the margins are not the answer to entrepreneurial questions of sustainability in business, several authors have suggested that the priority must instead be innovation at the business model level. Extensive reviews of hundreds of different approaches to business model innovation systematically categorise the innovations into boundaries of analysis, abstraction, and temporal relatedness (Pieroni, McAloone, and Pigosso, 2019); or outline the problems with change management, pitfalls, and actions (Geissdoerfer, Vladimirova, and Evans, 2018); and even look at the subject/discipline areas from which these models arise (Nosratabadi et. al., 2019). These extensive reviews suggest a building block for BD and AI enabled processes to search across business model innovations, cross checking costs and benefits based on the relative valuations or weights, whilst comparing and contrasting the ability of these innovations to truly internalise the externalities of entrepreneurial activities. In addition, AI and BD could help advance the theoretical and empirical understanding of real-world application of these business model innovations.

---

[2] See Saskia Bayerl et. al. (2013) for an application of PESTL to the role of the macro context in policing decisions in Europe, with reference to the link between technological and organisational change.

[3] For an example of dynamic application of SWOT analysis in the context of interdependencies between the local policy and the broader exogenous conditions, see Bevilacqua et. al. (2019).

Counterfactuals may be used to learn from "near" experiences (Costello & McCarthy, 1999), hence allowing for the tweaking of organizational, industry, market, and institutional factors to test which business models and strategies work best under which situations and contexts. As March (1991) points out, "what is good at a particular historical moment is not always good at another time. What is good for one part of an organization is not always good for another" (p. 73). AI and BD could learn from business model innovations discussed above, use existing firm data (or department-level data), and run counterfactuals, simulations, and models to find the innovations with least cost and most benefit in the transition to fully regenerative business practices. In addition, AI technologies go beyond the limits of machine learning by facilitating close interaction with and among humans via processes such as artificial swarm intelligence; enabling dozens, hundreds, or thousands of people to combine their insights simultaneously in a dynamic unified way. This can improve business decision making, particularly for business decisions that fall into the realm of 'known unknowns', by combining explicit knowledge of the known with tacit knowledge of individuals (Metcalf et al., 2019)[4].

Sustainable entrepreneurship expands on and combines (and re-combines) concepts and mythologies from the social entrepreneurship, eco/environmental entrepreneurship, and institutional entrepreneurship research paradigms under a common banner. In a competitive business landscape, sustainable entrepreneurs generate new and superior products, services, techniques and business models that are successful with the mainstream market and create market dynamics (at the meso / macro level) of social, societal, and environmental progress (Muñoz and Cohen, 2018). An 'inclusive innovation' approach to the development of new innovations in products/services, processes/business models, and supply-chain management can promote social sustainability in new projects and may be worth exploring to close the gap on alignment and collaboration between public (i.e., government and civil societies) and private interests (Kalkanci et al., 2019). After all, there is pressure on firms to adapt their practices, processes, and supply chains from both internal (e.g., shareholders and employees) and external (e.g., customers, regulators, and legislators) sources in light of the climate change movement, with possible spill over effects to related firms and industries (Reid and Toffel, 2009). The decision to be transparent in the reporting of sustainability performance is more likely when buyers are perceived to be committed to attaining and using this information as part of their

[4] For a detail discussion on swarm intelligence, see Kennedy and Eberhart (2001)

decision to consume, and also when organizations are in more profitable industries and countries with greenhouse gas regulations (Jira and Toffel, 2013). The complex interactions between networks of different actors in sustainable entrepreneurship (e.g., competitors, suppliers, local government, civil society, and NGOs, as Gibb and Adhikary 2000 suggest) requires new approaches to system analysis that can more accurately describe the whole picture; i.e., at the micro-, meso-, *and* macro-levels (Muñoz & Cohen, 2018). The collection, analysis, and dissemination of large-scale datasets across varied spatio-temporal scales will provide further innovation and ensure that more adequate conclusions are reached, based on a more complete informational environment of complex, dynamic, human ecosystems (Toma and Gheorghe, 1992). This will also enable specific contributions to the study of complex hierarchical systems that characteristically operate on different levels at varied spatio-temporal scales (Ulanowicz, 1997).

4. AI and BD in Sustainable Entrepreneurship

Sustainable Entrepreneurship – with its focus on creating sustainable business products, services, processes, and business models – can benefit greatly from AI-enabled approaches to BD analytics. Standard, theory-driven, statistical, and econometric approaches can struggle with scalability to BD unless underpinned by robust, formal, and structured data processing frameworks supported by reliable IT infrastructures and consistent coding frameworks as well as highly trained human resources to implement such approaches. AI, inductive, and data-driven approaches to BD analytics can act more freely, learning from experience by performing adaptive combinations and re-combinations of ideas and concepts which may themselves be vague or approximate (McCarthy, 2000). These approaches may require elaboration and tolerance for knowledge generation, adaptation, and evolution over time (McCarthy, 1998), and rapidly testing of these through methods such as counterfactual explorations and simulations (Costello and McCarthy, 1999). In entrepreneurship – and particularly sustainable entrepreneurship – information may be incomplete and plagued with uncertainty, which implies decision making based on nonmonotonic reasoning and logic (Reiter, 1988).

A key challenge in decision making is managements' inability to understand links between business processes, macro ecological processes, and boundary conditions. This extends into the difficulty of providing quantitative indicators that link corporate sustainability to a well-functioning ecosystem, and the failure to integrate 'systems thinking' beyond a single issue (for example, toxic emissions (Whiteman et al., 2013); or the firm itself (among others, Stubbs and Cocklin 2008; Bocken et. al. 2014)). Marshall and Toffel (2005) propose a hierarchy of sustainability "needs" (analogous to Maslow's 1943 hierarchy of needs) to help frame, plan, and monitor sustainability initiatives in a more systematic, familiar, and user-friendly way. Environmental Management Accounting has been classified as an innovative approach that supports environmentally beneficial decision-making in companies, linking it to planetary boundaries (Schaltegger, 2018). This approach is stronger than corporate social responsibility, because "corporate sustainability goes further by in addition considering planetary boundaries" Schaltegger, Etxeberria, and Ortas (2017, p. 114). But some scholars are highly critical of integrating a planetary-level approach to sustainability. For example, Gray (2010) stresses, that "any simple assessment of the relationship between a single organisation and planetary sustainability is virtually impossible. The relationship and interrelationships are simply too complex…and probably difficult to really conceptualise at anything below planetary and species levels" (p. 48). Antonini and Larrinaga (2017) also note that "[t]he increasing complexity of sustainability reporting has not been matched with a comparable level of methodological sophistication" (p. 124); questioning how a manager can report on individual firm-level success or activity within the context of planetary boundaries or planetary-level ecological processes. Beyond that, complex emergent patterns are notoriously difficult to identify (Kitto, 2008). However, pollution is concentrated, and there is a significant body of scientific work that describes the link between industrial pollution and self-reinforcing ecosystem feedback loops that drive additional emissions (Lenton et al., 2008). Heede (2014) explored historic emissions by tracing sources of industrial CO_2 and methane of the 90 largest corporate investor-owned or state-owned producers of fossil fuels and cement from 1854 to 2010. Those were responsible for 914 billion tonnes of CO_2-equivalents, and emissions tracked to the carbon majors represented 63% of global industrial CO_2 and methane. These are examples of classic super externalities – negative externalities whose effects are dispersed geographically and intertemporally. Echoing the fifth proposition suggested by Evans et. al. (2017) in a unified perspective on creating business models, Nosratabadi et. al. (2019) note that "internalizing externalities through the Product Service System also enables innovation towards sustainable business models" (p. 9). Until now, it has been impossible to accurately internalize those superexternalities, and instead, they have been largely ignored at the organizational level as something outside the economic modelling or decision-making process. AI and BD can bring those costs into the value chain, even from a planetary boundary and planetary level approach. Using advanced capacities for collecting and analysing information – perhaps authenticated and verified on the blockchain through distributed systems – AI and

BD offer the potential for businesses and their consumers to calculate and check the planetary cost of their processes and purchases.

In general, AI systems and BD analytics can help in the collection, generation and analysis of such quantitative indicators and help in dealing with the complexity, the non-linearity, and the role of time lags in eco-systems (Hastings, 2016). AI- (Pires de Lima and Marfurt, 2020) and BD-enabled approaches to global satellite data have proved successful in working with, merging, and making sense of remote sensing information from diverse and heterogenous sources and have been used to track biodiversity (Pettorelli et al., 2018; Pettorelli et al., 2016), land monitoring and conservation (Radočaj et al., 2020), crop monitoring (Wang et al., 2019), sustainable fisheries (Geronimo et al., 2018), and marine resource management (Levy et al., 2016). Novel combinations and re-combinations of various data sources and vague, imprecise methods of data query will enable the development new metrics and indicators for organizations to track progress in sustainability measures and strategy. Krikigianni et al. (2019) for example, combined DMSP[5] and VIIRS[6] earth observation imagery with statistical data on tourist activity at the country level to explore the impacts of tourism on light pollution (Krikigianni et al., 2019).

From a management perspective, any system requires identification of the current state and predictions for future system states based on the actions taken, while simultaneously attempting such actions that may lead to desirable outcomes (Hastings, 2016). In doing so, we often rely on heuristics due to the limited available knowledge. AI systems can help to improve the symbiosis of the micro perspective of firms and the macro perspective of the ecosystem and also combine (open) data and research from business and ecological fields. Such combination reduces the dysconnectivity between companies and the natural environment. Strategic planning therefore requires system behavioral understanding so as to provide a basis for decisions that are to be taken *today* as opposed to *tomorrow*. As Simon (1977) points out, the "objective in making predictions and projections into the future should be to provide a basis for the decisions that are to be taken today; tomorrow's decisions can and should be made on

---

[5] Defence Meteorological Satellite Program (DMSP), see available data products at https://www.ngdc.noaa.gov/stp/satellite/dmsp/index.html

[6] Visible Infrared Imaging Radiometer Suite (VIIRS), see available data products at https://earthdata.nasa.gov/earth-observation-data/near-real-time/download-nrt-data/viirs-nrt

the basis of the information available tomorrow. Some decisions are required today to provide lead time for tomorrow's actions" (Simon, 1977, p. 130).

AI has significant potential to become an important tool for sustainable supply chain management (SSCM) due to its complexity, interactions, and interdependencies among different sectors; the multiple sourcing and planning levels; access to logistics and information exchanges at all nodes and links in the chain; and the imperative of production challenges that require multiple decision variables and business practices such as lean management (Dash et al., 2019; Sitek and Wikarek, 2015). Strandhagen et. al. (2017) note that the goal of logistics is to seek "an appropriate service level and quality with the lowest possible costs" (p. 359). It is currently difficult, if not impossible, to incorporate entire logistics chains into holistic analyses of sustainable supply chain management. However, as automation and Industry 4.0 help with Logistics 4.0 (Strandhagen et. al., 2017), this could be facilitated by AI and BD enabled technology.

Thus, the capacity of decision-making requires handling of intricate interrelations in a complex (adaptive) system. For example, companies can profitably reduce greenhouse gas emissions in their supply chains (Plambeck, 2012). But sustainable approaches require not only predictive power to identify and predict supply and demand so as to optimize (or satisfy) the sourcing and design of better retailing and manufacturing strategies, but also to minimize waste, remanufacturing, recycling, disposal, and incineration; preventing the use of non-renewable resources; and reducing carbon emissions to achieve sustainable operations strategies (Sitek and Wikarek, 2015). Further, AI systems can also contribute by providing a framework for representing this knowledge and information for future SSCM decision making. Scholars have now the means by which to combine AI and BD systems with fields such as cybernetics, nonlinear science, and systems theory, and have produced myriad models of complex behaviour (see e.g., Holland, 1995; Mitchell, 2009; Page, 2011; Miller and Page, 2007 for an overview); for example, combining agent-based modelling (Bonabeau, 2002; Miller and Page, 2007), feedback loops (Sterman, 1994), or network theory (Newman, 2010; Newman et al., 2006). One possible approach is to treat firms as if they were organisms or open complex living systems. Because the new economy is organic in the sense of discovering and creating (Arthur, 2006) – knowledge and information, creativity are essential resources in a constantly changing world where ongoing ecological interactions call for additional responses, solutions, problems, possibilities as entities are not always stable (Torgler, 2019). Information processes are essential to the development of organisations whether in the biological or social world (Boulding, 1968). That is, in social systems, information, rather than being auxiliary to the system, is often the key commodity because adaptation, life cycle, and/or developmental processes rely on information feedback mechanisms. Adding more analytic tools and methods to the managerial/operational toolkit can contribute to an improvement in the field of sustainability science that tries to deepen our understanding of the interaction between nature and society – and its social needs (Carpenter et al., 2009; Kates, 2017).

Carpenter et al. (2009) emphasize the importance of focusing on the control of ecosystem services, exploring the effects of drivers including biodiversity and human feedback. Looking at companies is one way to identify people's revealed preferences in terms of higher sustainability performance, or a mix of ecosystem services – and which institutions, incentives, and regulations are effective in sustaining such flows and ecosystem services. AI can be harnessed in support of achieving environmentally sustainable human development, helping to improve the IOT and remote monitoring technologies of ecosystem services. Such monitoring is needed to evaluate trends and draw conclusions in regards to the relationships of social-ecological variables (Carpenter et al., 2009). For example, Schaltegger (2020) points out that zoonotic pathogens such as that responsible for the COVID-19 pandemic are a consequence of "not just bad luck or coincidence, but that they result from unsustainable economic and social practices relating to eco-systems" (p. 613). Enhanced monitoring and analysis of ecosystem practices may heighten our sensitivity to this genesis of pandemics, steering human decision making away from a quasi-brinkmanship interaction with the planet's biodiversity, carrying capacity, and sustainability. AI and BD hold important implications for how we will gather, store, and process information, and are central to both guiding sustainability transition to understand where we want to go and also to understanding how well we are doing at getting there (Clark, Crutzen and Schnellnhuber, 2005). Corporations play an important role in tracking performance and implementing observational systems. Further, evidence shows that AI may act as an enabler on 134 targets (79%) across all SDGs, generally through technological improvements and breakthroughs (Vinuesa et al., 2020). However, AI may equally have a negative influence on 59 (35%) of all SDGs (Vinuesa et al., 2020) and some benefits (costs) may (may not) be mutually exclusive. Hence, opportunity exists to capitalise on the positives of AI in SDGs and minimise/mitigate the negatives.

5. Challenges to Overcome

The dissemination of BD/AI-generated models and findings (in comparison to more standard/traditional, theory-driven research) will likely remain difficult for academic and non-academic (e.g., policymakers, industry stakeholders, entrepreneurs) audiences to engage with and accept. These approaches do not necessarily evolve from previous theories and research paradigms and more often than not, require specialist knowledge and skills to equip the user in their own practice (Lévesque et al., 2020). This highlights the importance of both education (school-, tertiary-, and practice-based) as well as open communication and engagement with key stakeholders including policy makers, managers, entrepreneurs, and start-up/innovation hubs. At the same time, self-awareness of the constraints and complexity of scalable BD/AI-enabled technologies is equally important to the pursuit of technological possibilities and entrepreneurial opportunities. In addition, the use of AI and BD tools needs to be cost-effective if it is to be actionable. As Freiberg et al. (2020) stress, "there are substantial costs to the data science resources needed to parse and use big data" (p. 31). One of those costs is the electricity required to power data centres, especially for complex processing. Yet, with ongoing feedback implemented in data centres themselves, it is possible to minimise energy consumption; Fernández-Cerero et al. (2020) test different software-driven decision-making approaches and methodologies for energy savings in large 'hyper scale' data centres, as well as in ordinary environments, finding that "[d]epending on the scenario, energy savings can vary from ~15% to as much as ~60%" (2020, p. 44060). With AI and BD acting as the data-centre manager adjusting the software running the data centres, these technologies could help regulate their own energy consumption required to fuel their operations.

History provides various examples in which the application of new techniques led to disastrous ecological outcomes due to a failure to understand the complexity of the system being manipulated. Scott (1998) discusses one good example from the field of scientific forestry that developed from around 1765 to 1800, mostly in Prussia and Saxony. At the time, the practice of both planned and unplanned felling led to an increasingly problematic shortage of wood. Thus, attempts were made to calculate precise measurements of forests, and new mathematical techniques were used for estimating the sustainable yield of commercial timber. However, this led to careful seeding, planting, and cutting of the forest in an attempt to create a resource that was easier to count and manipulate, measure and assess. This was a transformation from a chaotic old-growth forest into a new form of regimentation, a "neatly arranged construct of science. Practical goals had encouraged mathematical utilitarianism, which seemed, in turn, to promote geometric perfection as the outward sign of the well-managed forest; in turn the rationally ordered arrangement of trees offered new possibilities for controlling nature" (p. 15). In the short run, the approach was praised as an impressive success; the innovation spreading to France, England, the United States, and other countries. However, after the second generation of conifers were planned, a century of negative biological and commercial consequences became obvious in Germany. The whole nutrient cycle was out of order: "An exceptionally complex process involving soil building, nutrient uptake, and symbiotic relations among fungi, insects, mammals, and flora – which were, and still are, not entirely understood – was apparently disrupted, with serious consequences" (p. 20). Forest death was observed, leading to a production loss of 20 to 30 percent. As March (1990) stresses, the "pursuit of intelligence in organizations is never completely successful. To be sure, organizations sometimes manage to achieve impressive levels of intelligence; but organizational intelligence can also be equivocal, ephemeral, and chimerical" (p. 1). Unless practitioners and decision-makers are skilled synthesisers of information from different disciplines with a capacity for seeing second and third round effects (and beyond), many managers make decisions based on short term metrics because they are rewarded and praised in the short term; as such, top management commitment to encouraging more systematic and lifecycle thinking can improve sustainable decision making and entrepreneurship.

The growing use of AI and BD will require a better business understanding of potential biases (e.g., algorithmic and/or data), and therefore, operations management needs to understand how their business decision-making process might be affected by such biases. Kalkanci, Rahmani, and Toktay (2019), for example, suggest that "firms need to adopt inclusive design and development practices to avoid inadvertent exclusion of communities or hard-coding of (discriminatory) social attitudes into processes" (p. 2970). Here, a distinction between the ethics *of* AI and *ethical* AI is warranted: the ethics of AI is concerned with the moral behaviours of human AI designers and the impacts of AI on humanity, society, and the future of work; ethical AI is focused on developing AI that behave morally and exhibit ethical values and decision making (Siau & Wang, 2020). The ethics of AI and BD with algorithmic and/or data biases will likely be of growing concern to organizations. For example, data collected during the process of healthcare provision is rife with biases and disparities, and embedded in complex societal contexts, ethical issues, and moral dilemmas (McLennan et al., 2020). It is concerning to note limited mention of sustainability, harassment, or the ethics of data collection for AI in a recent survey of the current themes, breadth of topics, and depth of coverage in 31 standalone AI ethics university classes and 20 AI/ML technical courses in the United States (Garrett et al., 2020). Future AI applications will require – for the most part – more computing power and hence, greater resource consumption (Merrill, 2017) and hence, a lack of sustainable and systematic thinking in the design, development, and deployment of AI and BD systems may mean that such futuristic AI applications will not achieve viable commercial scalability. AI and related technologies will likely lead to a number of predictable and also unexpected (related to what humans tell it to optimise, learn, value, or prioritise – and more often than not, this will be unpredictable) ethical consequences requiring proactive engagement research on the privacy and ethics of AI / BD and related BD enabling technologies (Stahl and Wright, 2018). Consent, transparency, and data ownership are prominent ethical considerations for sustainable entrepreneurs to consider. A bottom-up, community-driven approach to the implementation of smart technologies such as AI, BD, and IOT could inform and guide decision making and opportunities for collaborative public-private business models achieving the best of both worlds: business development and customer/client engagement (Mark and Anya, 2019).

Explainable AI offers a solution to opening up the "black box" of AI / BD systems and providing greater transparency in AI decision making, perception, learning, and behaviours (Kerstholt et al., 2019). It is still unclear whether this may subsequently be used to fuel the development and refinement of theories of human perception, decision making, reasoning, and observed behaviours. Trust is a strong predictor of how systems may be used or mis-used (Chen and Barnes, 2014; de Visser et al., 2018). For instance, one consequence of too much trust can be misuse through overestimation of the technology's capabilities, resulting in complacency with respect to control; whilst low levels of trust results in underuse of systems, which potentially reduces efficiency and increases human workloads (Baker and Keebler, 2017) rather than supplementing them. Performance-related factors (e.g., reliability, false alarm rate, failure rate) and transparency of the AI system are particularly important determinants of trust development (Chen and Barnes, 2014). Propensity to trust (Stowers et al., 2017) and task load (Chen and Barnes, 2014) are also important human-related determinants of trust development, as are human expertise, personal characteristics (age, gender, personality), and sociocultural factors (Schaefer et al., 2016). We have witnessed repeated examples of organizational resistance to new technologies, and it will not be any different for AI, BD, and related future industry technologies. Perhaps a new approach may be required which places more focus on user/operator trust development and the co-evolution of tailored AI- and BD-enabled technologies over time.

6. Opportunities to Seize

The desire to predict the future is part of human nature, and we find many examples of this throughout history. Forecasting is the process of making predictions about the future based on historical and current data – most often using trend, indicator, and impact forecasts. Nevertheless, predicting the future is a complex task. It requires identification of variables that will change autonomously and inexorably, as well as understanding their distinction from variables that are constants, unchanging givens in a situation, to which other variables must adjust (Simon, 1977). Simon (1977) calls them "the hammer and the anvil that beat out the shape of the future" (p. 14). Quantitative forecasting models are usually applied to short or medium-term future scenarios and are used to predict future data depending on data from the past. They are suitable when sufficient historical data are available and when some of the patterns in the data are likely to continue (Schmidt 2020, p. 9), but not so good with increasing complexity, uncertainty, and risk of fat tail 'black swan' events; simply because – by their nature – black swan events do not occur often, and hence, there is not many (if any) observations of such events in historical datasets (Taleb, 2005), making it hard to learn from experience. One way of collecting more examples than available from direct observation and past experience is through the use of counterfactuals (Costello and McCarthy, 1999). AI can use this concept to explore the "what ifs" of black swan events under "similar" circumstances and incorporate the outcome of this simulation into the learnings taken from lived events and experience. An interesting project would be a side-by-side comparison of the data-driven, inductive AI approach to BD with the theory-driven, statistical, and econometric approach. This could help identify under which circumstances management practice and business direction should be based on a more structured, theory-driven approach – and when it should be informed by a more curiosity-driven, exploratory search – as well as the data characteristics required to support each approach.

Managers could use AI and other enabling technologies (e.g., BD, IOT, cloud and quantum computing) to analyse the enormous amount of data they collect about their business ecosystem. This may generate a better understanding when studying the strengths and limitations of different organizations and their processes. As Drucker (2001) has pointed out, "[j]ust as there are a great number of different structures for biological organizations, so there are a number of organizations for the social organism that is the modern institution. Instead of searching for the right organization, management needs to learn to look for, to develop, to test" (pp. 17-18). Artificial intelligence in this sense can enable development of fast, efficient, and scalable products and services; improved organisational processes and resource allocations; and optimised supply chains over time – in a dynamic 'online' and 'green friendly' fashion. However, the information provided can allow practitioners to go beyond a narrow, focused, operating organization towards exploration of opportunities; for example, investigating whether or not diversification can be helpful. Information systems can then be stronger in evaluating not only inside information but also outside information. For example, outside information can help in identifying and understanding your non-customers. Historically, CEOs have not relied heavily on new information; for example, Drucker (2002) has pointed out that for the CEO,

> new information has had little impact on how he or she makes decisions. This is going to have to change (p. 83) … Tomorrow's leader won't be able to lead by charisma. He or she will need to think through the fundamentals so that other people can work productively (p. 89) … "Increasingly, a CEO's job will be much more like the most complex job I know, which is running an opera. You have your stars and you can't give them orders; you have the supporting cast and the orchestra; you have the people who work behind the scenes; and you your audience. Each group is completely different. But the opera conductor has a score, and everybody has the same score. In a business you have to make sure all the various groups converge to produce the desired result. This is the key to understanding what's ahead (p. 90).

Entrepreneurship often involves decision making in complex problem spaces, and decision making in such environments implies acting based on imperfect information which may vary on many dimensions; for example, its social range, its genesis (e.g., routine, unanticipated, etc.), its scope, its differences in the process of decision-makings, its consequences, and its context (Smelser and Reed, 2012). Researchers have developed elaborate acronyms such as VUCA to describe our volatile, uncertain, complex, and ambiguous world. Unpredictability was already omnipresent – and then the pandemic hit. The crux is that now, in disruptive times, interpolation of historical data no longer allows predicting the future. Many more current contextual factors need to be incorporated into forecasting models to meet the complex and rapidly changing environmental conditions. As our world could change even more radically in the coming decades than in the past hundred years, quantitative forecasts are becoming increasingly complex and demanding. As March (1991) stresses, "[b]ecause of the links among environmental turbulence, organizational diversity, and competitive advantage, the evolutionary dominance of an organizational practice is sensitive to the relation between the rate of exploratory variation reflected by the practice and the rate of change in the environment" (p. 72). Likewise, the demand for those 'next generation' talents proficient in such technologies (Raff, 2018) is indicated by their high salaries and equally strong bargaining power (Belfield, 2020), and more generally, that of the digital natives whether learned or not (Helsper and Eynon, 2010). In just a few decades, a new world will have emerged – our great-grandchildren will not even be able to imagine the world as we know it today (Schmidt and Stoneham, 2020). Using artificial intelligence, in combination with other enabling technologies such as quantum computers, IT, and an extraordinary ubiquity of open BD datasets from which we may form insights, could help to provide better predictive models and therefore a better database for strategic discussions, thereby improving a start-up's (or organisation's) corporate intelligence. AI in management practices and economic analyses is most poised to contribute to academic literature by identifying mechanisms fundamental to systems and potentially enabling generalisation of mechanisms across systems and contexts; providing grounded applicability in the practice and analysis of business strategy and operations, as well as economic policy design (Gräbner, 2017). Looking for early-warning signals of complex human ecosystems moving towards or departing from periods of relative stability to wilder levels of uncertainty may be a suitable compromise given the inherent unpredictability of such complex ecosystems (Scheffer et al., 2012).

BD and in particular, open government data present significant opportunity for economic gain with focused business models and plans to generate new products and services (Zeleti et al., 2016). This public-private symbiosis also begs the question of whether governments may consider the establishment of formal public-private partnerships that provide value to both the private sector and the general public. The adoption of open government data initiatives is highly dependent on perceived benefits, organizational readiness, and external pressures (Wang and Lo, 2016); hence, working with government agencies to derive and answer domain-specific and meaningful policy questions is likely to provide mutual benefits, further supporting the development of an open (and BD) data industry. Freiberg et al. (2020), for example, develop a methodology to derive monetized environmental impact estimates to measure an organization's environmental impact from their operations based on the use of established environmental resources that are readily accessible in the public domain. This expansion of BD and AI systems provided directly by or in partnership with public organizations will require well-considered planning and implementation of integrated systems that simultaneously address concerns around AI governance and policy, providing support to businesses in AI research, development, and deployment, and equitable access to AI knowledge, information, training, and various largescale BD. For example, Wirtz and Müller (2019) present a conceptual AI framework with a general hierarchy of four AI technology layers. This model, while originally intended for public management of AI, can be used to guide "big picture" and systematic thinking to identify possible benefits as well as risks and opportunities in the AI and BD business landscape; including where your organization may leverage their existing practices, procedures, and knowledge to survive and thrive in such an environment. Other potentially fruitful applications of AI and BD in Sustainable Entrepreneurship come at the intersection of hardware and software. Over the past few years, major feats have been achieved by AI (in particular, ML and DL) methods – most of which were only possible with complementary enabling technologies; for example, the intersection of IOT and ISA-95 framework for AI decision making, monitoring, and analytics in process and manufacturing plants (Kuusk, 2019). We could also build from industry standards that offer prescriptive descriptions of safety systems' lifecycle planning and management such as the IEC 61508 and IEC 61511 Functional Safety standards (see e.g., Smith and Simpson 2010 for a comprehensive overview of the use and application of these and related standards). While scoped for personnel safety and hazard reduction in the context of industrial control systems, a design approach similar to the approach undertaken in Safety Instrumented System (SIS) design and verification could be applied to organizational systems that wish (or need) to attain industry-verified "sustainable identifiability". Using this information, and the concept of dividends/universal basic income based on the right to the wealth of the commons, AI can calculate in real time the "tax" or extent of externality a production cost/supply chain logistical decision would add to the global stock and flow of natural resources, and automatically redistribute resources accordingly. Common Wealth Dividends (Ranalli, 2021) or other such incentive schemes based on AI analysis and monitoring could also change the bottom line in entrepreneurial decision making and risk taking, and alter the incentive to develop more sustainable organizational practices. These standards and related regulatory bodies will need to continuously (and with precision) track, trace, and respond quickly to keep up with the fast-moving developments in AI, BD, and supplementary and enabling technologies. Having proved its efficacy in hazard management (e.g., clustering, classification, and sorting or making sense of hazard reports) (Garvin and Kimbleton, 2021), AI, BD, and related IT technologies could also enrich these standards by way of somewhat forced response and adaptation through research and development as AI- and BD-enabled analytics inevitably push social, economic, ethical, computational, and physical boundaries of what may once have been deemed highly unlikely or outright impossible.

Quantum-enabled or -inspired technologies and algorithms also promise to deliver non-insignificant computational speedups for certain processes above what is available with classic computers, enabling more complex data representations and analysis, which could support management in organizational strategy, decision making, and monitoring/evaluation. One aspect of this strategy may be sustainability. Quantum computers, logic, and information theory enables one to pose more imprecise queries, similar to those made by experts (Sriboonchitta et al., 2019), and may have wider applicability in reviving the study and advancement of knowledge management and expert systems (Bickley et al., 2020), which can be used to support and/or emulate sustainable entrepreneurship. Uncertainty is often a problem, as a choice may have a good outcome under one set of environmental condition, but a bad one under another, failing to observe Bayesian behavior (Simon, 1987). This can lead – as Simon (1987) pointed out – to nonproductive responses. Quantum computing and quantum information can enable more efficient exploration of complexity via testing and simulating various alternatives (Torgler, 2020). Advanced AI systems can shape managers' habits of attention and therefore contribute to the acquisition of intuition guided by problem-solving style. It can help call attention to problems and solutions that are less proximate or urgent, but sustainable in the long-run. Such sensitivity to the future can strengthen managerial intuition and suggests the potential to institutionalize attention (Simon, 1987). Knowledge, in the end, gives the system its direction (Simon, 1977).

7. Concluding Remarks

Organizations satisfy important social and psychological needs (Simon, 1977), and climate change is an urgent need that requires concerted and authentic efforts from top management to set organizational directions and drive sustainable progress (Henderson and Serafeim, 2020). AI, BD, and supporting/enabling IT technologies can help interpret and monitor the environment; identify the problems that need attention; design strategies; generate decisions; and if desired, even execute on the tactics. In this conceptual paper, we have explored implications, opportunities, and challenges of AI and BD in transforming the scope and practice of sustainable entrepreneurship. In general, there is much optimism for AI to help solve existing issues of more traditional statistical and econometric methods with the size and varied (heterogenous) nature of BD.

To summarise our contributions, we now return to the three research questions posed in the introduction and address them one by one.

How can AI and BD drive progress in sustainable entrepreneurship?

A key challenge in sustainable entrepreneurship is a failure to integrate 'systems thinking' beyond a limited number of issues, rather than taking the time to understand the relationship between business processes, macro ecological processes, boundary conditions, and tipping points. This requires the development of quantitative indicators to track progress in sustainability domains (e.g., social, environmental, health, and safety) and monitor for any adverse or maladaptive phenomena which may occur. AI and BD can drive progress in the monitoring, tracking, and analysis of complex ecosystems by integrating data, knowledge, and information from varied and largescale collections of BD databases (Costello and McCarthy, 1999). Managers could use this to their advantage; helping them analyse and prioritise the enormous amount of data they collect about their business ecosystem on a daily basis. This may allow organizations to generate a better understanding of the strengths and limitations of different organizations and their processes, adapting their business strategy/model to provide more sustainable competitive advantages.

As Yadav et al. (2007) stress, CEO attention is a critical driver of innovation and organizational focus, even when outcomes occur far in the future, and new products, services, and processes are distinct and novel. A CEO empowered by AI and BD is able to let curiosity and data guide the search for new risks and opportunities, freeing up CEO attention for decisions on formulating 'big picture' strategies and organizational direction, which often incorporate sustainability decisions. AI can use counterfactuals (Costello and McCarthy, 1999) to expand our learning beyond mere observation of the past, and explore the "what ifs" of unexpected, but devastating "black swan" climate events under "similar" circumstances – incorporating the outcomes from this simulation into the learnings taken from actual lived events and experience. In this way, AI and BD can help organizations appreciate, quantify, and reduce the impact of unknown unknowns and devastating black swan events (Nafday, 2009).

What are the major challenges to overcome and opportunities to seize?

Trust is a strong predictor of how new and existing sociotechnical systems may be used or mis-used. Human-AI trust development is partly driven by performance-related factors (e.g., reliability, robustness) and partly by the transparency of the AI system. Consent, privacy, and data ownership are important ethical considerations, particularly for sustainable entrepreneurs and public organizations utilising BD collected from mobile phones, social media, and other data sources with a 'personalized' element. Explainable AI offers one solution to opening up the "black box" of AI / BD systems and providing greater transparency in AI decision making, perception, learning, and behaviours – and hence, increasing trust and acceptance. Ultimately, it is both performance-related factors (e.g., reliability, false alarm rate, failure rate) and transparency of the system that are particularly important system-related determinants of human-AI trust development (Chen and Barnes, 2014). This may require trade-offs between the benefits derived from AI recommendations; the maintenance and continual update of complex knowledge structures (Bensoussan et al., 2009); and the incorporation of more transparent operations.

The dissemination of BD/AI-generated models and findings will likely remain difficult for academic and non-academic (e.g., policymakers, industry stakeholders, entrepreneurs) audiences to accept and engage with – at least in the short term – as these approaches do not necessarily evolve from previous theories and research paradigms (Lévesque et al., 2020). This highlights the growing importance of both education and open communication and engagement with key stakeholders including policy makers, managers, entrepreneurs, and start-up/innovation hubs. Sustainable entrepreneurs and organizations may gain a natural competitive advantage in their well-developed processes and practice in stakeholder engagement, their longer-term orientation/mindset, and a higher retention of long-term investors (Eccles et al. 2014), indicating an ability to collaborate, adapt, and customise their approach to complex ecological problems. An AI- and BD-enabled methodological toolkit would bolster their efforts and ability to capitalise on these natural competitive advantages.

What can organizations and entrepreneurs do to prepare, position, and find competitive advantages in an AI and BD future?

To prepare we must strategize by looking to and engaging with the market, our clients, and our customers for guidance; only then can we then proceed to develop viable and sustainable business models and plans. Through applied AI and other BD analytics, information- and data-intensive domains and industries could simultaneously provide greater value at less expense (Davenport and Ronanki, 2018). To help identify the scope for an organization's involvement, benefit from and support of various levels of the software/hardware AI and BD technology stack, it will be necessary to position the organizational skills, knowledge, and experience in the AI and BD technology spectrum by due consideration of the various layers of the AI technology infrastructure (Wirtz and Müller, 2019) and perhaps with reference to the ISA-95 system stack (Kuusk, 2019). Industry-verified "sustainable identifiability" is likely to be another area for substantial growth and application of AI and BD technologies. Leveraging the processes and procedures of functional safety standards and safety system lifecycle planning may be one such path towards "sustainable identifiability". Environmental Management Accounting may provide another suitable approach (Schaltegger, 2018). By and large, we would all like to better understand the new age we are entering, and to do so we need an antenna for what is coming and where we might go. The future comes fast and does not wait for us. We are on the edge of a dramatically different world brought about by technology that will push the boundaries of what is possible, building a different future. To reap the rewards of progress in AI, BD, and related technologies, we need to find ways to race with the emerging technologies and also identify ways to act in symbiosis with them. The demands of adapting to AI and BD are no different from the situation with past disruptive technologies such as the automobile, radio, and the Internet.

References

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.

Akerkar, R. (2019). *Artificial intelligence for business*. Springer.

Anand, K. S., & Giraud-Carrier, F. C. (2020). Pollution regulation of competitive markets. *Management Science*, 66(9), 4193-4206.

Antonini, C., & Larrinaga, C. (2017). Planetary boundaries and sustainability indicators. A survey of corporate reporting boundaries. *Sustainable Development*, 25(2), 123-137.

Arthur, W. B. (2006). T*he Nature of Technology: What It IS and How It Evolves*. Free Press.

Belfield, H. (2020). Activism by the AI community: Analysing recent achievements and future prospects. Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society,

Bevilacqua, C., Anversa, I. G., Cantafio, G., & Pizzimenti, P. (2019). Local clusters as "building blocks" for smart specialization strategies: a dynamic SWOT analysis application in the case of San Diego (US). *Sustainability*, 11(19), 5541.

Bickley, S. J., Chan, H. F., Schmidt, S. L., & Torgler, B. (2020). Quantum-sapiens: The quantum bases for human expertise, knowledge, and problem-solving. CREMA Working Paper, No. 2020-18.

Bocken, N. M., Short, S. W., Rana, P., & Evans, S. (2014). A literature and practice review to develop sustainable business model archetypes. *Journal of Cleaner Production*, 65, 42-56.

Bollinger, A. S., & Smith, R. D. (2001). Managing organizational knowledge as a strategic asset. *Journal of Knowledge Management*, *5*, 8-18.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. P*roceedings of the National Academy of Sciences*, *99*(suppl 3), 7280-7287.

Boulding, K. E. (1968). *Beyond economics: Essays on society, religion, and ethics*. Ann Arbor: University of Michigan Press.

Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review, 7*, 3-11.

Carpenter, S. R., Mooney, H. A., Agard, J., Capistrano, D., DeFries, R. S., Díaz, S., ... & Whyte, A. (2009). Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. *Proceedings of the National Academy of Sciences*, *106*(5), 1305-1312.

Charles, D., (2009), Leaping the efficiency gap. *Science* 325(5942): 804–811.

Chen, J. Y., & Barnes, M. J. (2014). Human–agent teaming for multirobot control: A review of human factors issues. I*EEE Transactions on Human-Machine Systems*, *44*(1), 13-29.

Clark, W. C., Crutzen, P. J., & Schnellnhuber, H. J. (2005). Science for Global Sustainability: Toward a New Paradigm., RWPO5-032, Harvard University, John K. Kennedy School of Government, Faculty Research Working Papers Series.

Costello, T., & McCarthy, J. (1999). Useful counterfactuals. L*inkoping Electronic Articles in Computer and Information Science, 3*, 1–28

Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability*, 14(3), 43-53.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108-116.

de Visser, E. J., Pak, R., & Shaw, T. H. (2018). From 'automation'to 'autonomy': the importance of trust repair in human–machine interaction. *Ergonomics*, *61*(10), 1409-1427.

Denrell, J., & March, J. G. (2001). Adaptation as information restriction: The hot stove effect. *Organization Science*, 12(5), 523-538.

Dowell, G., Hart, S., & Yeung, B. (2000). Do corporate global environmental standards create or destroy market value?. Management science, 46(8), 1059-1074.

Drucker, P. F. (2001). The essential drucker. Routledge.

Drucker, P.F. (2002). Managing in the next society. New York: St. Martin's Press

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63-71.

Eccles, R. G., Perkins, K. M., & Serafeim, G. (2012). How to become a sustainable company. *MIT Sloan Management Review*, *53*(4), 43-50.

Eccles, R. G., Ioannou, I., & Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. *Management Science*, 60(11), 2835-2857.

Evans, S., Vladimirova, D., Holgado, M., Van Fossen, K., Yang, M., Silva, E. A., & Barlow, C. Y. (2017). Business model innovation for sustainability: Towards a unified perspective for creation of sustainable business models. *Business Strategy and the Environment*, 26(5), 597-608.

Fernández-Cerero, D., Fernández-Montes, A., & Jakóbik, A. (2020). Limiting global warming by improving data-centre software. *IEEE Access*, 8, 44048-44062.

Freiberg, D., Park, D. G., Serafeim, G., & Zochowski, R. (2020). Corporate Environmental Impact: Measurement, Data and Information. Harvard Business School Accounting & Management Unit Working Paper, (20-098).

Garrett, N., Beard, N., & Fiesler, C. (2020). More Than" If Time Allows" The Role of Ethics in AI Education. Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society,

Garvin, T., & Kimbleton, S. (2021). Artificial intelligence as ally in hazard analysis. *Process Safety Progress*.forthcoming.

Geissdoerfer, M., Vladimirova, D., & Evans, S. (2018). Sustainable business model innovation: A review. *Journal of Cleaner Production*, 198, 401-416.

Geronimo, R. C., Franklin, E. C., Brainard, R. E., Elvidge, C. D., Santos, M. D., Venegas, R., & Mora, C. (2018). Mapping fishing activities and suitable fishing grounds using nighttime satellite images and maximum entropy modelling. *Remote Sensing, 10*(10), 1604.

Gibb, A., & Adhikary, D. (2000). Strategies for local and regional NGO development: combining sustainable outcomes with sustainable organizations. *Entrepreneurship & Regional Development*, *12*(2), 137-161.

Gräbner, C. (2017). The Complementary Relationship Between Institutional and Complexity Economics: The Example of Deep Mechanismic Explanations. *Journal of Economic Issues, 51*(2), 392-400.

Graves, S. (2021). Reflections on the Evolution of Operations Management. *Management Science*, forthcoming.

Gray, R. (2010). Is accounting for sustainability actually accounting for sustainability… and how would we know? An exploration of narratives of organisations and the planet. A*ccounting, Organizations and Society*, 35(1), 47-62.

Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review*, *20*(4), 986-1014.

Hart, S. L., & Dowell, G. (2011). Invited editorial: A natural-resource-based view of the firm: Fifteen years after. *Journal of Management*, *37*(5), 1464-1479.

Hastings, A. (2016). Timescales and the management of ecological systems. *Proceedings of the National Academy of Sciences*, *113*(51), 14568-14573.

Heede, R. (2014). Tracing anthropogenic carbon dioxide and methane emissions to fossil fuel and cement producers, 1854–2010. *Climatic Change*, *122*(1), 229-241.

Helsper, E. J., & Eynon, R. (2010). Digital natives: where is the evidence? *British Educational Research Journal, 36*(3), 503-520.

Henderson, R., & Serafeim, G. (2020). Tackling climate change requires organizational purpose. A*EA Papers and Proceedings*, *110*, 177-80).

Hlupic, V., Pouloudi, A., & Rzevski, G. (2002). Towards an integrated approach to knowledge management:'hard','soft'and 'abstract'issues. *Knowledge and Process Management, 9*(2), 90-102.

Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Basic Books.

Hörisch, J., Schaltegger, S., & Freeman, R. E. (2020). Integrating stakeholder theory and sustainability accounting: A conceptual synthesis. *Journal of Cleaner Production*, 275, 124097.

Hu, Z., Cao, J., & Hong, L. J. (2012). Robust simulation of global warming policies using the DICE model. *Management Science*, *58*(12), 2190-2206.

Ibrahim, D. (2016). An overview of soft computing. *Procedia Computer Science, 102*, 34-38.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577-586.

Jira, C., & Toffel, M. W. (2013). Engaging supply chains in climate change. *Manufacturing & Service Operations Management*, *15*(4), 559-577.

Joyce, A., & Paquin, R. L. (2016). The triple layered business model canvas: A tool to design more sustainable business models. *Journal of Cleaner Production*, 135, 1474-1486.

Kalkanci, B., Rahmani, M., & Toktay, L. B. (2019). The role of inclusive innovation in promoting social sustainability. *Production and Operations Management, 28*(12), 2960-2982.

Kates, R. W. (2017). Sustainability science. In: D. Richardson, N. Castree, M. F. Goodschild, A. Kobayashi, W. Liu, & R. A Marston (Eds.), T*he International Encyclopedia of Geography*. John Wiley & Sons, Ltd.

Kennedy, J. & Eberhart, R. C. (2001). *Swarm intelligence*. Elsevier.

Kerstholt, J., Barnhoorn, J., Hueting, T., & Schuilenborg, L. (2019). *Automation as an Intelligent Teammate: Social Psychological Implications*. http://essay.utwente.nl/77177/

Kimble, H. J. (2008). The quantum internet. *Nature, 453*(7198), 1023-1030.

King, B., & McDonnell, M. H. (2012). Good firms, good targets: The relationship between corporate social responsibility, reputation, and activist targeting. Corporate Social Responsibility in a Globalizing World: Toward Effective Global CSR Frameworks. Edited by Kiyoteru Tsutsui and Alwyn Lim.(Forthcoming).

King, B., & McDonnell, M. H. (2012). Good firms, good targets: The relationship between corporate social responsibility, reputation, and activist targeting. Corporate Social Responsibility in a Globalizing World: Toward Effective Global CSR Frameworks. Edited by Kiyoteru Tsutsui and Alwyn Lim.(Forthcoming).

Kiron, D., Kruschwitz, N., Haanaes, K., & Velken, I. V. S. (2012). Sustainability nears a tipping point. *MIT Sloan Management Review*, *53*(2), 69-74.

Kitto, K. (2008). High end complexity. *International Journal of General Systems*, *37*(6), 689-714.

Kleindorfer, P. R., Singhal, K., & Van Wassenhove, L. N. (2005). Sustainable operations management. *Production and Operations Management*, *14*(4), 482-492.

Kok, J. N., Boers, E. J., Kosters, W. A., Van der Putten, P., & Poel, M. (2009). Artificial intelligence: definition, trends, techniques, and cases. *Artificial Intelligence, 1*, 270-299.

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2016). How artificial intelligence will redefine management. *Harvard Business Review*, *2*, 1-6.

Krikigianni, E., Tsiakos, C., & Chalkias, C. (2019). Estimating the relationship between touristic activities and night light emissions. *European Journal of Remote Sensing, 52*(sup1), 233-246.

Kuusk, A. G. (2019). Aligning IIoT and ISA-95 to Improve Asset Management in Process Industries. World Congress on Engineering Asset Management,

Lenton, T. M., Held, H., Kriegler, E., Hall, J. W., Lucht, W., Rahmstorf, S., & Schellnhuber, H. J. (2008). Tipping elements in the Earth's climate system. *Proceedings of the National Academy of Sciences, 105*(6), 1786-1793.

Lévesque, M., Obschonka, M., and Nambian, S. (2021). Pursuing impactful entrepreneurship research using artificial intelligence. *Entrepreneurship Theory and Practice*, forthcoming. Levy, G., Vigundelli, S., & Gower, J. (2016). Ocean remote sensing for sustainable resources. *International Journal of Remote Sensing, 37*(9), 1977-1980.

Lockett, A., Thompson, S., & Morgenstern, U. (2009). The development of the resource-based view of the firm: A critical appraisal. *International journal of management reviews, 11*(1), 9-28.

March, J. G. (1991). Exploration and exploitation in organizational learning. O*rganization Science*, 2(1), 71-87.

March, J. G. (1999). The Pursuit of Organizational Intelligence. Blackwell Business.

March, J. G. (2010). *The ambiguities of experience*. Cornell University Press.

Mark, R., & Anya, G. (2019). Ethics of using smart city AI and big data: The case of four large European cities. *The ORBIT Journal, 2*(2), 1-36.

Marshall, J. D., & Toffel, M. W. (2005). Framing the elusive concept of sustainability: A sustainability hierarchy. *Environmental science & technology, 39*(3), 673-682.

Maslow, A. H. (1943). A theory of human motivation. *Psychological review, 50*(4), 370.

Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping humans in the loop: pooling knowledge through artificial swarm intelligence to improve business decision making. *California Management Review*, *61*(4), 84-109.

McCarthy, J. (1998). Elaboration tolerance. Elaboration tolerance. In COMMON SENSE 98, Symposium On Logical Formalizations of Commonsense Reasoning.

McCarthy, J. (2000). Approximate objects and approximate theories. in: A.G. Cohn, F. Giunchiglia, B. Selman (Eds.), KR2000: Principles of Knowledge Representation and Reasoning, Proceedings of the Seventh International conference, Morgan Kaufman, pp. 519–526

McLennan, S., Lee, M. M., Fiske, A., & Celi, L. A. (2020). AI ethics is not a panacea. *The American Journal of Bioethics, 20*(11), 20-22.

Merrill, N. (2017). Better Not to Know? The SHA1 Collision & the Limits of Polemic Computation. Proceedings of the 2017 Workshop on Computing Within Limits,

Miller, J. H., & Page, S. E. (2007). *Complex adaptive systems: An introduction to computational models of social life*. Princeton University press.

Mitchell, M. (2009). *Complexity: A guided tour*. Oxford University Press.

Muñoz, P., & Cohen, B. (2018). Sustainable entrepreneurship research: Taking stock and looking ahead. *Business Strategy and the Environment, 27*(3), 300-322.

Newell, A. (1990). *Unified Theories of Cognition*. Harvard University Press.

Newman, M. E. (2010). N*etworks: An Introduction*. Oxford University Press.

Newman, M E., Barabási, A. L., & Watts, D. J. (Eds.). (2006). T*he structure and dynamics of networks*. Princeton University Press.

Nosratabadi, S., Mosavi, A., Shamshirband, S., Kazimieras Zavadskas, E., Rakotonirainy, A., & Chau, K. W. (2019). Sustainable business models: A review. *Sustainability*, 11(6), 1663.

Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: a new era has begun. *Small Business Economics*, 55, 529-539.

Obschonka, M., Lee, N., Rodríguez-Pose, A., Eichstaedt, J. C., & Ebert, T. (2020). Big data methods, social media, and the psychology of entrepreneurial regions: capturing cross-county personality traits and their impact on entrepreneurship in the USA. *Small Business Economics, 55*(3), 567-588.

Page, S. E. (2011). *Diversity and complexity*. Princeton University Press.

Pettorelli, N., Schulte to Bühne, H., Tulloch, A., Dubois, G., Macinnis-Ng, C., Queirós, A. M., Keith, D. A., Wegmann, M., Schrodt, F., & Stellmes, M. (2018). Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. *Remote Sensing in Ecology and Conservation, 4*(2), 71-93.

Pettorelli, N., Wegmann, M., Skidmore, A., Mücher, S., Dawson, T. P., Fernandez, M., Lucas, R., Schaepman, M. E., Wang, T., & O'Connor, B. (2016). Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. *Remote Sensing in Ecology and Conservation, 2*(3), 122-131.

Pieroni, M. P., McAloone, T. C., & Pigosso, D. C. (2019). Business model innovation for circular economy and sustainability: A review of approaches. *Journal of cleaner production*, 215, 198-216.

Pires de Lima, R., & Marfurt, K. (2020). Convolutional neural network for remote-sensing scene classification: Transfer learning analysis. *Remote Sensing, 12*(1), 86.

Plambeck, E. L. (2013). OM Forum—Operations management challenges for some "cleantech" firms. M*anufacturing & Service Operations Management*, *15*(4), 527-536.

Radočaj, D., Obhođaš, J., Jurišić, M., & Gašparović, M. (2020). Global Open Data Remote Sensing Satellite Missions for Land Monitoring and Conservation: A Review. *Land, 9*(11), 402.

Raff, E. (2018). Growing and Retaining AI Talent for the United States Government. *arXiv preprint arXiv:1809.10276*.

Reid, E. M., & Toffel, M. W. (2009). Responding to public and private politics: Corporate disclosure of climate change strategies. *Strategic Management Journal, 30*(11), 1157-1178.

Reiter, R. (1988). Nonmonotonic reasoning. *Exploring artificial intelligence*, 439-481.

Renalli, B. (2021), *Common Wealth Dividends: History and Theory*, Palgrave Macmillan (forthcoming).

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., ... & Foley, J. A. (2009). A safe operating space for humanity. *Nature*, *461*(7263), 472-475.

Saskia Bayerl, P., Jacobs, G., Denef, S., van den Berg, R.J., Kaptein, N., Birdi, K., Bisogni, F., Cassan, D., Costanzo, P., Gascó, M., Horton, K., Jochoms, T., Mirceva, S., Krstevska, K., van den Oord, A., Otoiu, C., Rajkovchevski, R., Reguli, Z., Rogiest, S., Stojanovski, T., Vit, M. and Vonas, G. (2013), "The role of macro context for the link between technological and organizational change", *Journal of Organizational Change Management*, Vol. 26 No. 5, pp. 793-810.

Schaefer, K. E., Chen, J. Y., Szalma, J. L., & Hancock, P. A. (2016). A meta-analysis of factors influencing the development of trust in automation: Implications for understanding autonomy in future systems. *Human Factors*, *58*(3), 377-400.

Schaltegger, S. (2018). Linking environmental management accounting: A reflection on (missing) links to sustainability and planetary boundaries. *Social and Environmental Accountability Journal*, *38*(1), 19-29.

Schaltegger, S. (2020). Unsustainability as a key source of epi-and pandemics: conclusions for sustainability and ecosystems accounting. Journal of Accounting & Organizational Change.

Schaltegger, S., Etxeberria, I. Á., & Ortas, E. (2017). Innovating corporate accounting and reporting for sustainability–attributes and challenges. *Sustainable Development*, 25(2), 113-122.

Schaltegger, S., Hörisch, J., & Freeman, R. E. (2019). Business cases for sustainability: A stakeholder theory perspective. *Organization & Environment*, 32(3), 191-212.

Scheffer, M., Carpenter, S. R., Lenton, T. M., Bascompte, J., Brock, W., Dakos, V., Van de Koppel, J., Van de Leemput, I. A., Levin, S. A., & Van Nes, E. H. (2012). Anticipating critical transitions. *Science, 338*(6105), 344-348.

Schmidt, S. L. (Ed.). (2020). *21st Century Sports: How Technologies Will Change Sports in the Digital Age*. Springer.

Schmidt, S. L., & Stoneham, K. (2020). Beyond 2030: What Sports Will Look like for the Athletes, Consumers, and Managers. In 21st Century Sports (pp. 293-301). Springer.

Scott, J. C. (1998). *Seeing like a state: How certain schemes to improve the human condition have failed*. Yale University Press.

Serafeim, G., Zochowski, T. R., & Downing, J. (2019). Impact-Weighted Financial Accounts: the missing piece for an impact economy. Harvard Business School.

Sharma, S., & Vredenburg, H. (1998). Proactive corporate environmental strategy and the development of competitively valuable organizational capabilities. S*trategic Management Journal*, *19*(8), 729-753.

Sheng, J., Amankwah-Amoah, J., Khan, Z., & Wang, X. (2020). COVID-19 Pandemic in the New Era of Big Data Analytics: Methodological Innovations and Future Research Directions. *British Journal of Management*.

Short, J. L., & Toffel, M. W. (2010). Making self-regulation more than merely symbolic: The critical role of the legal environment. *Administrative Science Quarterly, 55*(3), 361-396.

Siau, K., & Wang, W. (2020). Artificial intelligence (AI) ethics: ethics of AI and ethical AI. *Journal of Database Management (JDM), 31*(2), 74-87.

Siler, W. (2005). *Fuzzy expert systems and fuzzy reasoning*. Wiley-Interscience. https://doi.org/10.1002/0471698504

Simon, H. A. (1977). *The New Science of Management Decision*. Prentice-Hall, Inc.

Simon, H. A. (1987). Making management decisions: The role of intuition and emotion. *Academy of Management Perspectives*, 1(1), 57-64.

Simon, H. A. (1995). Explaining the ineffable: Al on the topics of intuition, insight and inspiration. In Fourteenth International Joint Conference on Artificial Intelligence. San Francisco: Morgan Kaufmann (pp. 939-48).

Sitek, P., & Wikarek, J. (2015). A hybrid framework for the modelling and optimisation of decision problems in sustainable supply chain management. *International Journal of Production Research*, *53*(21), 6611-6628.

Sitkin, S. B., Sutcliffe, K. M., & Schroeder, R. G. (1994). Distinguishing control from learning in total quality management: a contingency perspective. *Academy of Management Review*, *19*(3), 537-564.

Sriboonchitta, S., Nguyen, H. T., Kosheleva, O., Kreinovich, V., & Nguyen, T. N. (2019). Quantum approach explains the need for expert knowledge: on the example of econometrics. International Conference of the Thailand Econometrics Society,

Stahl, B. C., & Wright, D. (2018). Ethics and privacy in AI and big data: Implementing responsible research and innovation. *IEEE Security & Privacy, 16*(3), 26-33.

Sterman, J. D. (1994). Learning in and about complex systems. *System Dynamics Review*, *10*(2-3), 291-330.

Stowers, K., Oglesby, J., Sonesh, S., Leyva, K., Iwig, C., & Salas, E. (2017). A Framework to Guide the Assessment of Human–Machine Systems. *Human Factors: Journal of Human Factors and Ergonomics Society*, *59*(2), 172-188.

Strandhagen, J. O., Vallandingham, L. R., Fragapane, G., Strandhagen, J. W., Stangeland, A. B. H., & Sharma, N. (2017). Logistics 4.0 and emerging sustainable business models. *Advances in Manufacturing*, 5(4), 359-369.

Stubbs, W., & Cocklin, C. (2008). Conceptualizing a "sustainability business model". *Organization & Environment*, 21(2), 103-127.

Taleb, N. (2005). The black swan: Why don't we learn that we don't learn. *NY: Random House*.

Tiefenbeck, V., Goette, L., Degen, K., Tasic, V., Fleisch, E., Lalive, R., & Staake, T. (2018). Overcoming salience bias: How real-time feedback fosters resource conservation. *Management Science*, 64(3), 1458-1476.

Toma, L., & Gheorghe, E. (1992). Equilibrium and disorder in human decision-making processes:: Some methodological aspects within the new paradigm. *Technological Forecasting & Social Change, 41*(4), 401-422. https://doi.org/10.1016/0040-1625(92)90046-V

Torgler, B. (2019). Opportunities and challenges of portable biological, social, and behavioral sensing systems for the social sciences. In G. Foster (Ed.), *Biophysical measurement in experimental social science research*. Academic Press, pp. 197-224.

Torgler, B. (2020). Big Data, Artificial Intelligence, and Quantum Computing in Sports. In: S. Schmidt (Ed.), *21st Century Sports* (pp. 153-173). Springer Nature.

Ulanowicz, R. E. (1997). *Ecology, the ascendent perspective / Robert E. Ulanowicz*. Columbia University Press.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Nerini, F. F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature communications, 11*(1), 1-10.

von Bloh, J., Broekel, T., Özgun, B., & Sternberg, R. (2019). New (s) data for entrepreneurship research? An innovative approach to use big data on media coverage. *Small Business Economics*, 1-22.

Wang, H.-J., & Lo, J. (2016, 2016/01/01/). Adoption of open government data among government agencies. *Government Information Quarterly, 33*(1), 80-88. https://doi.org/https://doi.org/10.1016/j.giq.2015.11.004

Wang, L., Zhang, G., Wang, Z., Liu, J., Shang, J., & Liang, L. (2019). Bibliometric analysis of remote sensing research trend in crop growth monitoring: A case study in China. *Remote Sensing, 11*(7), 809.

Whiteman, G., Walker, B., & Perego, P. (2013). Planetary boundaries: Ecological foundations for corporate sustainability. *Journal of Management Studies*, *50*(2), 307-336.

Zeleti, F. A., Ojo, A., & Curry, E. (2016). Exploring the economic value of open government data. *Government Information Quarterly, 33*(3), 535-551.

Zhang, S. X., & Van Burg, E. (2019). Advancing entrepreneurship as a design science: developing additional design principles for effectuation. *Small Business Economics*, 1-20.