

Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research and Practice

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Abstract

As far back as the industrial revolution, great leaps in technical innovation succeeded in transforming numerous manual tasks and processes that had been in existence for decades where humans had reached the limits of physical capacity. Artificial Intelligence (AI) offers this same transformative potential for the augmentation and potential replacement of human tasks and activities within a wide range of industrial, intellectual and social applications. The pace of change for this new AI technological age is staggering, with new breakthroughs in algorithmic machine learning and autonomous decision making engendering new opportunities for continued innovation. The impact of AI is significant, with industries ranging from: finance, retail, healthcare, manufacturing, supply chain and logistics all set to be disrupted by the onset of AI technologies. The study brings together the collective insight from a number of leading expert contributors to highlight the significant opportunities, challenges and potential research agenda posed by the rapid emergence of AI within a number of domains: technological, business and management, science and technology, government and public sector. The research offers significant and timely insight to AI technology and its impact on the future of industry and society in general.

Keywords: Artificial intelligence; AI; Cognitive computing; Expert system; Machine learning; Research agenda

1. Introduction

Artificial Intelligence (AI) is a concept that has been part of public discourse for decades, often depicted within science fiction films or debates on how intelligent machines will take over the world relegating the human race to a mundane servile existence in supporting the new AI order. Whilst this picture is a somewhat caricature-like depiction of AI, the reality is that artificial intelligence has arrived in the present and many of us interact with it every day. AI technology is no longer the realm of futurologists but an integral component of the business model of many organisations and a key strategic element in the plans for many sectors of business, medicine and governments on a global scale.

The literature has offered a number of definitions of AI each encapsulating the key concepts of non-human intelligence programmed to perform specific tasks. Russell & Norvig, (2016) defined the term AI to describe systems that mimic cognitive functions generally associated with human attributes such as learning, speech and problem solving. A more detailed and perhaps elaborate characterisation presented in Kaplan & Haenlein (2019) is - AI as the ability of a system to independently interpret and learn from external data to achieve specific outcomes via flexible adaptation. The recent study by Juniper Research (2019) describes AI as an integrated computer program that utilises mathematics, algorithms and data to solve problems and perform tasks that would normally be performed by humans. The common thread amongst all these definitions is the increasing capability of machines to perform some of the roles currently performed by humans within the workplace and society in general.

The ability for AI to overcome some of the computationally intensive, intellectual and even creative limitations of humans, opens up new application domains within manufacturing, healthcare, finance, education and marketing with resulting impacts on productivity and performance. AI enabled systems within organisations are expanding rapidly, transforming business and manufacturing, extending their reach into what would normally be seen as exclusively human domains (Daugherty & Wilson 2018; Miller 2018). The era of AI systems has progressed to levels where: autonomous vehicles, chatbots, autonomous planning and scheduling, gaming, translation, medical diagnosis and even spam fighting can be performed via machine intelligence. However, whilst this disruptive potential for some may be the next stage of an exciting technological phase, for other sections of society impacted by the redesign of business models and change of interaction, AI is a threat to society, a job killer and a backward step for the human race (Cellan-Jones 2014; Rawlinson 2015). Society generally is yet to fully grasp many of the ethical and economic considerations associated with AI and its wider impact on human life and culture (Duan et al. 2019).

The probabilistic analysis of the economic impact of AI and automation has been assessed by the Swiss based World Economic Forum (WEF) where they predict that 20% of existing UK jobs could be impacted by AI technologies. This figure is greater in emerging economies such as China and India, where the level rises to 26% due to the greater scope for technological change within the manufacturing sector. AI technologies are predicted to drive innovation and economic growth creating 133 million new jobs globally by 2022, contributing 20% of GDP within China by 2030 (WEF 2018). The recent report from Juniper Research highlighted that global spending on AI technologies within the consumer retail sector alone is predicted to reach \$12bn by 2023, a significant rise from the current figure of \$3.6bn. The research also highlighted the increasing use of AI in the form of chatbots for customer service applications, where these deployments could realise annual savings of \$439m globally by 2023, up from \$7m in 2019 (Juniper Research 2019). Retail giants such as Amazon and Walmart have been experimenting with AI for some time applying the technology to demand forecasting and supply chain fulfilment. Walmart's store of the future - Intelligent Retail Lab (IRL) is testing AI with analytics to trigger the need to respond when customers pick the last item and then track the store's ability to quickly restock the product. The Walmart IRL AI systems are supported by cameras and sensors installed throughout the store that transmit 1.6 TB of data per second to data centres and linked supply chain fulfilment (Forbes 2019). The use of AI technology within this sector can only increase as other firms respond to the competition from these market leaders.

Whilst the benefits of greater levels of AI adoption within many sectors of the global economy are felt in the context of greater efficiency, improved productivity and reliability, this picture of positive innovation is not universally welcomed across the world. Robots have replaced well over half of the jobs in manufacturing in recent decades and this trend is likely to continue. Studies have analysed the impact of this significant change, developing a narrative of a changing jobs market that is predicted to focus humans further up the value chain on more creative and cognitive orientated roles in support of AI technologies (DIN & DKE, 2018; Jonsson & Svensson, 2016). However, is this particular vision of an AI future a universal one across the globe within both developed and emerging markets? The fact that AI has the capacity to replace many rules-based and repetitive tasks, means that significant numbers of jobs that traditionally would be undertaken within emerging market economies will be lost. There are benefits of AI being centred within the developed economies where new higher skilled jobs are likely to be created, but there is a potential scenario where AI could displace millions of jobs within emerging economies. This is likely to have significant impact within Asia and Africa as traditional low skilled jobs are replaced by intelligent machine thereby damaging growth and worker livelihoods within these economies (BBC 2019). The potential impact on humans and economies from greater strides toward AI, is still being worked out, what is clear is that there are likely to be winners and losers and that decision makers need to be strategic in their outlook for the future.

The study brings together the collective insight from the workshop titled "*Artificial Intelligence (AI): Emerging Challenges, Opportunities, and Agenda for Research and Practice*" held at the School of Management, Swansea University, UK on 13th June 2019. Contributions were received from expert collaborators from industry and academia to highlight the significant opportunities, challenges and potential research agenda posed by the rapid emergence of AI within a number of domains: technological, business and management, science and technology, government and public sector. This research is presented as offering significant and timely insight to AI technology, its potential application and its impact on the future of industry and society.

The remaining sections of this study are organised as follows: *Section 2* presents many of the key debates and overall themes within the literature; *Section 3* details the multiple perspectives on AI technologies from the expert contributors; *Section 4* presents a discussion on the key AI related topics relating to the challenges opportunities and research agendas presented by the expert contributors. The study is concluded in *section 5*.

2. Debate Within Existing Literature

This section synthesises existing AI focussed literature and elaborates on the key themes listed in Table 1. Studies included in this section were identified using Scopus database, using the following combination of keywords: (TITLE ("Artificial intelligence") AND TITLE ("Advantages" OR "Benefit" OR "Opportunities" OR "Limitation" OR "Challenge" OR "Barriers" OR "Shortcoming" OR "agenda" OR "Research Direction". Existing research reviewed for this article is categorised in the following major themes: AI and Decision Making; Application Domains; Data and Information; Challenges.

Table 1. Themes in AI Research

Theme	Details	Citations
AI and decision making	Artificial Neural Network	Abarca-Alvarez et al., 2018; Abbot & Marohasy, 2013; Baldassarre et al., 2017; Cleophas & Cleophas, 2010; Kahn, 2017
	Deep Learning	Anderson, 2019; Lassau et al., 2019; Nguyen & Shetty, 2018; Tizhoosh & Pantanowitz, 2018; Stead, 2018; Thrall et al., 2018
	Algorithmic	Dreyer & Allen, 2018; Kahn, 2017; Risse, 2019; Stead, 2018; Varga-Szemes, et al., 2018; Zandi et al., 2019
	Learning Systems	Duan et al., 2019; Glauner et al., 2017; Walton, 2018; Wang et al., 2015
	Decision Support Systems	Abarca-Alvarez et al., 2018; Milano et al., 2014; Schulz & Nakamoto, 2013
	Deep Neural Networks	Milano et al., 2014; Mitchell, 2019; Duan et al., 2019
Application domains	Robotics	Edwards, 2018; Erikson & Salzmman-Erikson, 2016; Gupta & Kumari 2017
	Healthcare and informatics	Beregi et al., 2018; Cheshire, 2017; Cleophas & Cleophas, 2010; Combi, 2017; Dreyer & Allen, 2018; Gupta & Kumari, 2017; Houssami et al., 2017; Kahn, 2017; Khanna et al., 2013; Lassau et al., 2019; Nguyen & Shetty, 2018; Stead, 2018; Thesmar et al., 2019; Thrall et al. 2018; Varga-Szemes et al., 2018; Xu et al., 2019; Zandi et al., 2019
	Digital Imaging	Beregi et al., 2018; Gupta & Kumari, 2017; Kahn, 2017; Lassau et al., 2019; Nguyen & Shetty, 2018; Stead, 2018;
	Education and Policy	Arlitsch & Newell, 2017; Chaudhri et al., 2013; Mikhaylov et al., 2018; Nguyen, 2018; Yoon & Baek, 2016; Yoon, 2016;
	Manufacturing	DIN & DKE 2018; Haeffner & Panuwatwanich 2017; Jain and Mosier 1992; Jonsson & Svensson 2016; Katz 2017; Kumar 2017; Kusiak 1987; Lee et al. 2018; Lee 2002; Li 2018; Li et al. 2017; Löffler & Tschiesner 2013; Makridakis 2018; Muhuri et al. 2019; Nikolic et al. 2017; Parveen, 2018; Wang et al. 2015; Wang & Wang 2018; Yang et al. 2017; Zhong et al. 2017a
Data & information	Big Data	Abarce-Alvarez et al., 2018; Beregi et al., 2018; Duan et al., 2019; Rubik & Jabs, 2018; Schulz & Nakamoto, 2013; Stead, 2018; Thrall et al., 2018; Xu et al., 2019
	Data Visualisation	Olshannikova et al. 2015; Zheng et al. 2016; Zhong et al. 2017b

2.1. AI and decision making

Aspects of the literature have considered the use and impact of AI based systems for decision-making applications. These studies include topics such as: Artificial Neural Networks; Deep Learning;

Algorithmic; Learning Systems; Decision Support Systems; Deep Neural Networks and Expert Systems. Studies have applied artificial neural techniques to data analysis and pattern recognition problems. The research by Abbot and Marohasy (2013) examines the application of neural networks based on AI for forecasting monthly rainfall in Nebo, Queensland, Australia. The study highlighted the benefits in combining multiple non-linear relationships using neural networks to predict rainfall patterns one month in advance. This application of AI was posited as directly contributing to the prediction of flood risk weather patterns. The research by Cleophas and Cleophas (2010) applied back propagation (BP) artificial neural networks for data analysis based on layers of artificial neurons. The authors compared the predicted body surface from a hidden layer BP neural network to the body surface demonstrating that BP neural networks can predict clinical diagnoses with similar accuracies to other methods.

Deep Learning is a term that seems to be gaining traction within the literature and is associated with machine learning architectures and concepts but at a greater level and depth of neural network layers. Studies have posited the potential benefits of Deep Learning applications in areas of digital pathology and related medical applications, whilst cognisant of the limitations of this technology in terms of human reasoning and interpretation (Glauner et al. 2017; Stead 2018; Tizhoosh and Pantanowitz 2018). The study by Anderson (2019) analysed the potential of combining Deep Learning technology with Electrocardiogram (ECG) applications to detect patients with reduced left ventricular ejection fraction (rLVEF). Detecting patients with rLVEF would be helpful in patients for whom echocardiography or other imaging modalities are not available or too expensive. Early diagnosis of rLVEF could directly impact patient diagnosis and mortality levels.

Studies have posited the benefits of utilising deep neural networks to improve the use of AI. However, the use of deeper networks and big datasets is unlikely to develop *meaning* in the human context, requiring further interdisciplinary research to unlock this area (Mitchell, 2019).

2.2. Application domains

The AI literature has identified a number of separate domains in which the technology can be applied: Manufacturing, supply chain, Robotics, Healthcare, Digital Imaging, Education, and Government.

Studies have analysed the impact of AI and its potential to replace humans via intelligent automation within manufacturing, supply chain, production and even the construction industry (Kusiak, 1987; Lee et al., 2018; Muhuri et al., 2019; Parveen, 2018). Existing factory processes will be increasingly subject to analysis to ascertain whether they could be automated (Lee, 2002; Löffler & Tschiesner, 2013; Yang et al., 2017). AI centric technologies will be able to monitor and control processes in real time offering significant efficiencies over manual processes (Jain and Mosier, 1992; Lee et al., 2018; Zhong et al., 2017a). Organisations have posited the benefits of integrating AI technologies in the development of intelligent manufacturing and the smart factory of the future (Li et al., 2017; Nikolic et al., 2017). The literature has generally moved on from the somewhat dated concepts of AI based machines replacing all human workers. Studies have recognised the realistic limits of the continuing drive to automation, highlighting a more realistic *human in the loop* concept where the focus on AI is to enhance human capability, not replace it (Katz, 2017; Kumar, 2017). Humans are likely to move up the value chain to focus on design and integration related activities as part of an integrated AI, machines and human based workforce (DIN & DKE, 2018; Jonsson & Svensson, 2016; Makridakis, 2018; Wang et al., 2015; Wang & Wang, 2018). Manufacturing organisations are likely to use AI technologies within a production environment where intelligent machines are socially integrated within the manufacturing process, effectively functioning as co-workers for key tasks or to solve significant problems (Haefner & Panuwatwanich 2017).

Khanna et al. (2013) emphasised the importance of AI in healthcare, particularly in medical informatics. There is a growing need for new technologies that understand the complexities of hospital operations and provide the necessary productivity gains in resource usage and patient service delivery. AI has the potential to offer improved patient care and diagnosis as well as interpretation of medical imaging in

areas such as radiology (Dreyer and Allen, 2018; Kahn 2017). Screening for breast cancer and other related conditions could be more accurate and efficient using AI technology. The research by Houssami et al. (2017) analyses the use of AI for breast cancer (BC) screening highlighting its potential in reducing false-positives and related human detection errors. The study acknowledges some of the interrelated ethical and societal trust factors but the boundaries of reliance on AI and acceptable *human in the loop* involvement is still to be developed. The application of AI and related digital technologies within public health is developing fast. However, collection, storage, and sharing of AI technology derived large data sets, raises ethical questions connected to governance, quality, safety, standards, privacy and data ownership (Zandi et al., 2019). Thesmar et al. (2019) posited the benefits of utilising AI technology for insurance claims within healthcare. Claim submission, claim adjudication and fraud analysis can hugely benefit from the use of AI.

Education and information search is an area where the literature has identified the potential benefits of AI technology solutions. Chudhri et al. (2013) discussed application of AI in education to improve teacher effectiveness and student engagement. The study analysed the potential of AI within education in the context of intelligent game-based learning environments, tutoring systems and intelligent narrative technologies. The relevance of libraries in the modern technology era has received focus within the literature. Arlitsch and Newell (2017) discussed how AI can change library processes, staffing requirements and library users. It is important for libraries to focus on human qualities and the value add of human interaction integrated with AI to provide a richer user experience. The study by Mikhaylov et al. (2018) considered the use of AI capabilities from the perspective of educating the public on policy and a more effective mechanism for high uncertainty environments.

2.3. Data and information

The topic of big data and its integration with AI has received significant interest within the wider literature. Studies have identified the benefits of applying AI technologies to big data problems and the significant value of analytic insight and predictive capability for a number of scenarios (Rubik and Jabs, 2018). Health related studies that have analysed the impact and contribution of big data and AI and big arguing that these technologies can greatly support patient health based diagnosis and predictive capability (Beregi et al. 2018; Schulz and Nakamoto 2013). Big Data Analytics (BDA) develops the methodological analysis of large data structures, often categorised under the terms: volume, velocity, variety, veracity and value adding. BDA combined with AI has the potential to transform areas of manufacturing, health and business intelligence offering advanced incites within a predictive context (Abarca-Alvarez et al., 2018; Shukla et al., 2018; Spanaki et al., 2018; Wang & Wang, 2016).

Organisations are increasingly making use of data visualisation tools and methods and to make sense of their big data structures. In scenarios where the limitations of human perception and cognition are taken into account, greater levels of understanding and interpretation can be gained from the analysis and presentation of data using AI technologies (Olshannikova et al. 2015). The analysis and processing of complex heterogeneous data is problematic. Organisations can extract significant value and key management information from big data via intelligent AI based visualisation tools (Zheng et al. 2016; Zhong et al. 2017b).

2.4. Challenges

The implementation of AI technologies can present significant challenges for organisations as the scope and depth of potential applications increases and the use of AI becomes mainstream. Table 2 presents a number of categories of types of challenge.

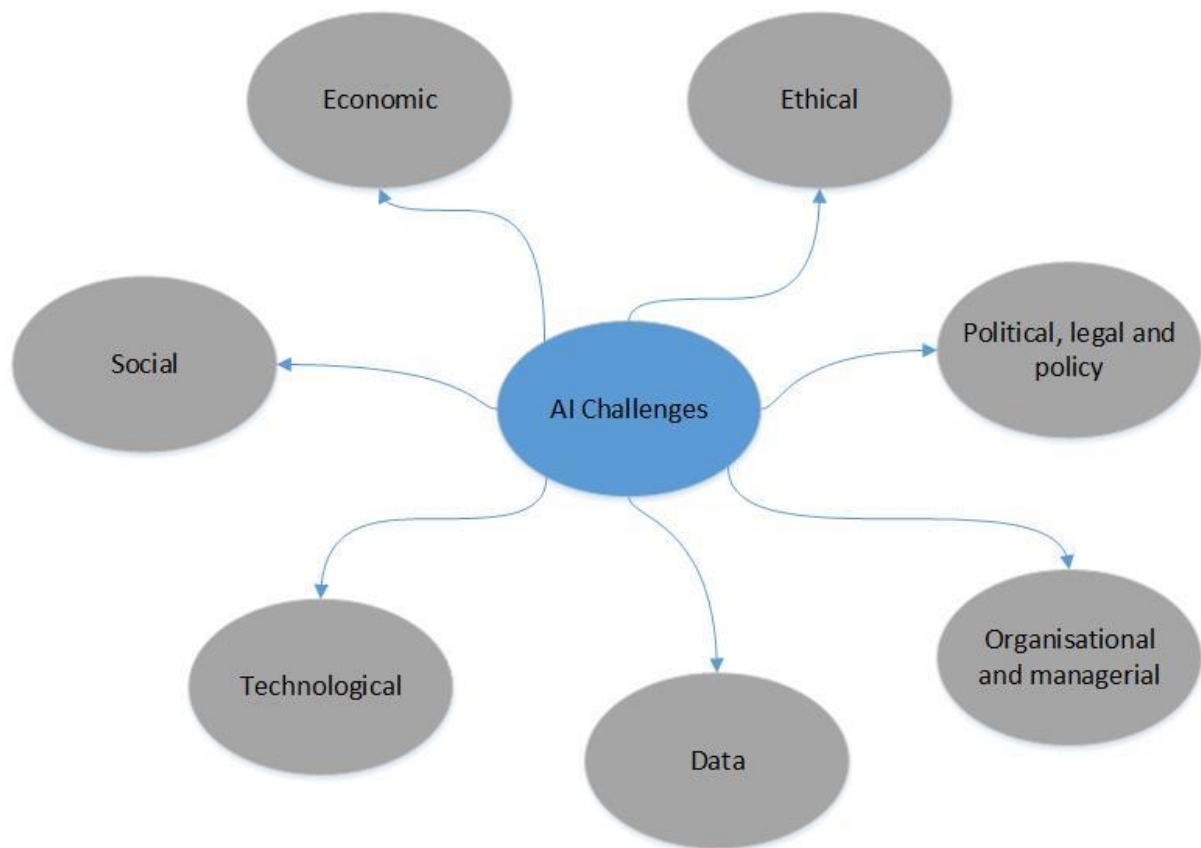


Figure 1 : AI Challenges

2.4.1. Social challenges

Patient/Clinician Education; Cultural barriers; Human rights; country specific disease profiles, insufficient innovation social driving forces, unrealistic expectations towards AI technology, country specific medical practices and insufficient knowledge on values and advantages of AI technologies

The increasing use of AI is likely to challenge cultural norms and act as a potential barrier within certain sectors of the population. The research by Xu et al. (2019) highlighted the challenges that AI will bring to healthcare in the context of the change in interaction and patient education. This is likely to impact the patient as well as the clinician. The study highlighted the requirement for clinicians to learn to interact with AI technologies in the context of healthcare delivery and for patient education to mitigate the fear of technology for many patient demographics (Xu et al., 2019). The study by Thall et al. (2017) argued that culture is one of the key barriers of AI adoption within radiology, as patients may have a reticence to interact with new technologies and systems. Social challenges have been highlighted as potential barriers to the further adoption of AI technologies. The study by Sun and Medaglia (2019) identified social challenges relating to unrealistic expectations towards AI technology and insufficient knowledge on values and advantages of AI technologies. Studies have discussed the social aspects of potential job losses due to AI technologies. This specific topic has received widespread publicity in the media and debated within numerous forums. The study by Risse (2019) proposed that AI creates challenges for humans that can affect the nature of work and potential influence on people's status as participants in society. Human workers are likely to progress up the value chain to focus on utilising human attributes to solve design and integration problems as part of an integrated AI and human centric workforce (DIN & DKE, 2018; Jonsson & Svensson, 2016; Makridakis, 2018; Wang et al., 2015; Wang & Wang, 2018).

2.4.2. Economic challenges

Affordability of required computational expenses; high treatment costs for patients, high cost and reduced profits for hospitals. Ethical challenges including: lack of trust towards AI-based decision, lack of trust towards AI based decision, and unethical use of shared data

The mass introduction of AI technologies could have a significant economic impact on organisations and institutions in the context of required investment and changes to working practices. The study by Tizhoosh and Pantanowitz (2018) focused on the affordability of technology within the medical field arguing that AI is likely to require substantial financial investment. The study highlights the impact on pathology laboratories where current financial pressures may be exacerbated by the additional pressures to adopt AI technologies. The study by Sun and Medaglia (2019) identified a number of healthcare related economic challenges arguing that the introduction of IA based technologies is likely to influence the profitability of hospitals and potentially raise treatment costs for patients.

AI technologies have the potential to affect many sectors within the global economy. The McKinsey report on the economic impact of AI (Bughin et al., 2018) develops a narrative of how organisations are likely to adopt this technology and the potential challenges for key markets during the transition. The report analyses: organisation behaviours and how they are likely to adopt AI; disruption during transition as firms experience the economic gains and losses; country specific impacts where AI could potentially widen the gap amongst emerging and developed markets as well as the rich and poor (Bughin et al., 2018).

2.4.3. Data challenges

Lack of data to validate benefits of AI solutions; quantity and quality of input data; transparency and reproducibility; dimensionality obstacles; insufficient size of available data pool, lack of data integration and continuity, lack of standards of data collection, format and quality, lack of data integration and continuity, lack of standards for data collection, format and quality.

The challenges of AI and integration with big data have been discussed within a number of studies. There is a need for new and efficient technologies to handle the large volume, variety and velocity of big data (Khanna et al., 2013). The study by Xu et al. (2019) identified data challenges of using AI in cancer genomics. The study identified the challenge in validating the benefits of AI solutions and challenges in obtaining statistically significant patient outcome data. Challenges surrounding transparency and reproducibility were also highlighted, especially in the context of acceptability relating to public perception. Challenges within computational pathology and the use of AI have been discussed in Tizhoosh and Pantanowitz (2018). The study highlighted the complexities of using artificial neural networks in the interpretation of imagery and the dimensionality obstacle. The research undertaken by Varga-Szemes et al. (2018) highlighted the challenges of machine learning within a cardiac imaging context, positing a need to create a standardised format to share data across different institutions. The current position on standards and data structures can be a barrier to application of AI. The study by Sun and Medaglia (2019) highlighted a number of data challenges surrounding the use of data and data integrity. As the transition to AI technologies matures, these challenges will need to be resolved to ensure full confidence by all stakeholders.

2.4.4. Organisational and managerial challenges

Realism of AI; Better understanding of needs of the health systems; organisational resistance to data sharing, lack of in-house AI talent, threat of replacement of human workforce; lack of strategy for AI development, lack of interdisciplinary talent, threat to replacement of human workforce

The transition toward adopting AI technologies presents a number of organisational and managerial challenges that have strategic implications for firms. Tizhoosh and Pantanowitz (2018) highlighted the significant challenges in the implementation of AI. Success relating to AI adoption is likely to be evidence based, will depend on ease of use, financial return on investment and trust. The study by Khanna et al. (2013) highlighted the need for AI researchers to better understand the most urgent current

needs of health systems and design technologies in order to address them. Current AI systems need to use more sophisticated technologies where human vs computer interaction can be improved and connected with the flow of information. Studies have highlighted that organisations face significant issues where the lack of a strategy relating to implications of AI could affect critical business areas and fail to address concerns from the human workforce (Sun and Medaglia, 2019).

2.4.5. Technological and technology implementation challenges

Non-Boolean nature of diagnostic tasks; adversarial attacks; Lack of transparency and interpretability; design of AI systems; AI safety; specialization and expertise; big data; architecture and lack of ability to read unstructured data.

Studies have analysed the non-boolean nature of diagnostic tasks within healthcare and the challenges of applying AI technologies to the interpretation of data and imaging. The study by Tizhoosh and Pantanowitz (2018) highlighted the fact that humans apply cautious language or descriptive terminology, not just binary language whereas AI based systems tend to function as a black box where the lack of transparency acts as a barrier to adoption of the technology. These points are reinforced in Cleophas and Cleophas (2010) and Kahn (2017) where the research identified a number of limitations of AI for imaging and medical diagnosis, thereby impacting clinician confidence in the technology. Cheshire (2017) discusses the limitation of medical AI-loopthink. The term loopthink is defined as a type of implicit bias, which does not perform correct reappraisal of information or revision of an ongoing plan of action. Thus, AI would disfavour qualitative human moral principles. Weak loopthink refers to the intrinsic inability of computer intelligence to redirect executive data flow because of its fixed internal hard writing, un-editable sectors of its operating system, or unalterable lines of its programme code. Strong loopthink refers to artificial intelligence suppression due to internalisation of the ethical framework.

Challenges exist around the architecture of IA systems and the need for sophisticated structures to understand human cognitive flexibility, learning speed and even moral qualities (Edwards 2018; Baldassarre et al. 2017). The research undertaken by Sun and Medaglia (2019) reviewed the technological challenges of algorithm opacity and lack of ability to read unstructured data. The Thall et al. (2017) study considered the challenge of a limited pool of investigators trained in AI and radiology. This could be solved by recruiting scientists with backgrounds in AI, but also by establishing educational programs in radiology professional services (Nguyen et al., 2018; Thall et al., 2017). The study by Varga-Szemes et al. (2018) highlighted that machine learning algorithms should be created by machine learning specialists with relevant knowledge of medicine and a clear understanding of possible outcomes and consequences. Mitchell (2019) highlighted that AI systems do not yet have the essence of human intelligence. AI systems are not able to understand the situations we experience and derive the right meaning from it. This barrier of meaning makes current AI systems vulnerable in many areas but particularly to hacker attacks titled - “adversarial examples”. In these kinds of attacks, a hacker can make specific and subtle changes to sound, image or text files, which will not have a human cognitive impact but could cause a program to make potentially catastrophic errors. As the programs do not understand the inputs they process and outputs they produce, they are susceptible to unexpected errors and undetectable attacks. These impacts can influence domains such as: computer vision, medical image processing, speech recognition and language processing (Mitchell, 2019).

2.4.6. Political, legal and policy

Copyright issues; governance of autonomous intelligence systems, responsibility and accountability, privacy/safety; national security threats from foreign-owned companies collecting sensible data, lack of rules of accountability in the use of AI, costly human resources still regally required to account for AI based decision, lack of official industry standards of AI use and performance evaluation, country specific legal standards.

Gupta and Kumari (2017) discussed legal challenges connected to AI-responsibility when errors occur using AI systems. Another legal challenge of using AI systems can be the issue of copyrights. Current legal framework needs significant changes in order to effectively protect and incentivise human

generated work (Zatarain, 2017). Wirtz et al. (2019) focused on challenges of implementing AI in public sectors. The study analysed the concept of AI law and regulations to control governance including autonomous intelligence systems, responsibility and accountability and privacy/safety. Sun and Medaglia (2019) analysed the challenges of applying AI within the public sector by using a case study approach. The study analysed the scope of changes and impact on the public sector in the context of: Political, legal and policy challenges include national security threats from foreign-owned companies.

2.4.7. Ethical challenges

Responsibility and explanation of decision made by AI; processes relating to AI and human behaviour, compatibility of machine versus human value judgement, moral dilemmas and AI discrimination

Researchers have discussed the ethical dimensions of AI and implications for greater use of the technology. The study by Sun and Medaglia (2019) identified a number of ethical challenges relating to the adoption of AI, highlighting the lack of trust in AI-based decisions and unethical use of shared data as key areas to focus on. The rapid pace of change and development of AI technologies increases the concerns that ethical issues are not dealt with formally. It is not clear how ethical and legal concerns especially around responsibility and analysis of decisions made by AI based systems can be solved. Adequate policies, regulations, ethical guidance and legal framework to prevent the misuse of AI should be developed (Duan et al., 2019). The study by Gupta and Kumari (2017) reinforces many of these points highlighting the ethical challenges relating to greater use of AI, data sharing issues and inoperability of systems.

2.5. Future Opportunities

AI technology in all its forms is likely to see greater levels of adoption within organisations as the range of applications and levels of automation increase. Studies have estimated that by 2030, 70 percent of companies are likely to have adopted some form of AI technology within their business processes or factory setting (Bughin et al., 2018). Studies have posited the benefits of greater levels of adoption of AI within a range of applications, with manufacturing, healthcare and digital marketing developing significant academic interest. The factories of the future are likely to utilise AI technology extensively, as production becomes more automated and industry migrates to a more intelligent platform using AI and cyber physical systems (Wang & Wang, 2018). Within healthcare related studies, researchers have proposed new opportunities for the application of AI within medical diagnosis and pathology where mundane tasks can be automated with greater levels of speed and accuracy (Tizhoosh and Pantanowitz., 2018). Via the use of human biofield technology, AI systems linked to sensors placed on and near the human body can monitor health and well-being (Rubik and Jabs, 2018). AI technologies will be able to monitor numerous life-signs parameters via Body Area Networks (BANs) where remote diagnosis requiring specialised clinical opinion and intervention will be checked by a human (Hughes et al., 2012).

AI technologies have been incorporated into marketing and retail where big data analytics are used to develop personalised profiles of customers and their predicted purchasing habits. Understanding and predicting consumer demand via integrated supply chains is more critical than ever and AI technology is likely to be a critical integral element. The study by Juniper Research (2018) predicts that demand forecasting using AI will more than treble between 2019 and 2023 and that chatbot interactions will reach 22bn in the same year from current levels of 2.6bn. The study highlights that firms are investing heavily in AI to improve trend analysis, logistics planning and stock management. AI based innovations such as the virtual mirror and visual search are set to improve the customer interaction and narrow the gap between the physical and virtual shopping experience (Juniper Research, 2018).

Researchers have argued for the more realistic future where the relationship between AI is likely to transition toward a *human in the loop* collaborative context rather than an industry-wide replacement of humans (Katz, 2017; Kumar, 2017). The study by Stead (2018) asserts the importance of establishing a partnership where the AI machine will calculate and/or predict and humans will explain and decide

on the appropriate action. Humans are likely to focus on more value add activities requiring design, analysis and interpretation based on AI processing and outputs. Future organisations are likely to focus on creating value from an integrated human and AI collaborative workforce (Jonsson & Svensson, 2016; Makridakis, 2018; Wang et al., 2015; Wang & Wang, 2018).

3. Multiple Perspectives from Invited Expert Contributors

This section has been structured by employing an approach adopted from Dwivedi et al. (2015) to present consolidated yet multiple perspectives on various aspects of AI from invited expert contributors. We invited each expert to set out their contribution in up to 3-4 pages, which are compiled in this section in largely unedited form, expressed directly as they were written by the authors. Such an approach creates an inherent unevenness in the logical flow but captures the distinctive orientations of the experts and their recommendations at this critical juncture in the evolution of AI (Dwivedi et al., 2015).

3.1. Technological Perspective

3.1.1. Explainability and AI systems - John S. Edwards

Explainability is the ability to explain the reasoning behind a particular decision, classification or forecast. It has become an increasingly hot topic recently in both theory and practice of AI and machine learning systems.

Challenges

Explainability has been an issue ever since the earliest days of AI use in business in the 1980s. This accounted for much of the early success of rule-based expert systems, where explanations were straightforward to construct, compared to frame-based systems, where explanations were more difficult, and neural networks, where they were impossible. At their inception, neural networks were unable to give explanations except in terms of weightings with little real-world relevance. As a result, they were often referred to as “black box” systems. More recently, so-called deep learning systems (typically neural networks with more than one hidden layer) make the task of explanation even more difficult.

The implied “gold standard” has been that when a person makes a decision, they can be asked to give an explanation, but this human explanation process is a more complex one than is usually recognized in the AI literature, as indicated by Miller (2019). Even if a human explanation is given that appears valid, is it accurate? Face-to-face job interviews are notorious for the risk of being decided on factors (such as how the interviewee walks across the room) other than the ones the panel members think they are using. This is related to the difficulty of making tacit knowledge explicit.

There is also a difference between the “how” explanations that are useful for AI system developers and the “why” explanations that are most helpful to end-users. Preece (2018) describes how this too was recognized in the earliest days of expert systems such as MYCIN. Nevertheless some of the recent AI literature seems unaware of this; it is perhaps significant that the machine learning literature tends to use the term interpretability rather than explainability. There are, however, many exceptions such as Adadi and Berrada (2018), who identify four reasons for explanation: to justify, to control, to improve and to discover.

An important change in context is that governments are now introducing guidelines for the use of any type of automated decision-making systems, not just AI systems. For example, the European Union’s General Data Protection Regulation (GDPR) Article 22 states “The data subject shall have the right not to be subject to a decision based solely on automated processing”, and the associated Recital 71 gives the data subject “the right...to obtain an explanation of the decision reached after such assessment and to challenge the decision”. Similarly, the UK government has introduced a code of conduct for the use of “data-driven technology” in health and social care (Anonymous, 2018). In regulated industries, existing provisions about decision-making, such as outlawing “red-lining” in evaluating mortgage or

loan applications, which were first enshrined in law in the US as far back as the 1960s, also apply to AI systems.

Opportunities

People like explanations, even when they are not really necessary. It is not a major disaster if Netflix® recommends a film I don't like to me, but even there a simple explanation like "because you watched <name of film/TV programme>" is added. Unfortunately, at the time of writing, it doesn't matter whether I watched that other film/TV programme all the way through or gave up after five minutes. There is plenty of scope for improving such simple explanations. More importantly, work here would give a foundation for understanding what really makes a good explanation for an automated decision, and this understanding should be transferable to systems which need a much higher level of responsibility, such as safety-critical systems, medical diagnosis systems or crime detection systems.

Alternatively, a good explanation for an automated decision may not need to be judged on the same criteria that would be used for a human decision, even in a similar domain. People are good at recognizing faces and other types of image, but most of us do not know how we do it, and so cannot give a useful explanation. Research into machine learning-based image recognition is relatively well advanced. The work of researchers at IBM and MIT on understanding the reasoning of generative adversarial networks (GANs) for image recognition suggests that "to some degree, GANs are organizing knowledge and information in ways that are logical to humans" (Dickson, 2019). For example, one neuron in the network corresponds to the concept "tree". This line of study may even help us to understand how we humans do some tasks.

Contrary to both of these views, London (2019) argues that in medical diagnosis and treatment, explainability is less important than accuracy. London argues that human medical decision-making is not so different from a black box approach, in that there is often no agreed underlying causal model: "Large parts of medical practice frequently reflect a mixture of empirical findings and inherited clinical culture." (p.17) The outputs from a deep learning black box approach should therefore simply be judged in the same way, using clinical trials and evidence-based practice, and research should concentrate on striving for accuracy.

Lastly, advances in data visualization techniques and technology offer the prospect of completely different approaches to the traditional "explanation in words".

Research Agenda

We offer suggestions for research in five linked areas.

- Can explanations from a single central approach be tailored to different classes of explainee? Explanation approaches are typically divided into transparency and post hoc interpretation (see e.g. Preece, 2018), the former being more suitable for "how" explanations, the latter for "why". Is it possible to tailor explanations from a single central approach to different classes of explainee (developers, end-users, domain experts...)? For example, a visualization approach for end-users that would allow drill-down for more knowledgeable explainees?
- What sort of explanation best demonstrates compliance with statute/regulation? For example, how specific does it have to be? UK train travellers often hear "this service is delayed because of delays to a previous service", which is a logically valid but completely useless explanation. Do there need to be different requirements for different industry sectors? What form should the explanation take - words, pictures, probabilities? The latter links to the next point.
- Understanding the validity and acceptability of using probabilities in AI explanation. It is well-known that many people are poor at dealing with probabilities (Tversky and Kahneman, 1983). Are explanations from AI systems in terms of probabilities acceptable? This is widely used in the healthcare sector already, but it is not clear how well understood even the existing explanations are, especially in the light of the comments by London mentioned in the previous section.

- Improving explanations of all decisions, not just automated ones. Can post hoc approaches like the IBM/MIT work on GANs produce better explanations of not only automated decisions, but also those made by humans?
- Investigating the perceived trade-off between transparency and system performance. It is generally accepted that there is an inverse relationship between performance/accuracy and explainability for an AI system, and hence a trade-off that needs to be made. For example, Niel Nickolaisen, vice president and CTO at human resource consulting company O.C. Tanner observed: “I agree that there needs to be some transparency into the algorithms, but does that weaken the capabilities of the [machine learning] to test different models and create the ensemble that best links cause and effect?” (Holak, 2018). Does this trade-off have to be the case? Could a radical approach to explanation be an outlier to the trade-off curve?

3.1.2. Information theoretic challenges, opportunities & research agenda – Paul Walton

AI is introducing new ways in which organisations can process information. This note discusses AI in the context of the limitations in this processing predicted by information theory (Walton, 2018) and highlights implications for the implementation, adoption and use of AI.

Challenges

The implementation of AI is different from traditional technology implementation and introduces a new set of challenges. These challenges are driven by a combination of the following factors: the changing nature of the business environment, the nature of AI and machine learning (ML) themselves, and underlying information theory limitations that apply to all information processing but in specific ways to AI/ML.

Entities (like people, animals, organisations or computer systems) that interact with their environments are subject to information-related selection pressures that drive trade-offs between information measures—the pace and friction of information processing and the quality of the information produced (Walton, 2014; 2015ab). These selection pressures are different in different environments, so different information ecosystems have developed with different ways of exchanging information (eg languages, jargon, computer protocols). Ecosystems have their own conventions for information processes and measures driven by the trade-offs. The conventions of different ecosystems mean that each approaches information processing from a different viewpoint and has its own set of inherent limitations with respect to information—good enough for the selection pressures of the ecosystem but not necessarily more widely (Walton, 2017).

This concept of a viewpoint applies at different levels—to an organisation, its departments, computer systems, people and beyond. Humans, for example, have different forms of perception and inference (Mercier and Sperber, 2017) that operate in different ways and from different viewpoints. Usually the brain manages to create an integrated overall picture from these but beneath the surface impression there are gaps that magic, for example, exploits (Macknik and Martinez-Conde, 2011). Are similar gaps possible for the implementation of AI in organisations? AI is becoming pervasive (since it is just another set of computing techniques that any developer or product supplier can use) and is increasingly being included in components as diverse as smart assistants, modules for enterprise products, widely available cloud libraries and bespoke data-science-driven applications; in addition, it is already being applied to numerous different business use cases. Critically, in subsets of these components, the data science may be handled independently, for example by product or cloud suppliers, with different viewpoints. So the following question arises: *how can the inferences delivered by different AI components be integrated coherently when they may be based on different data, and subject to different ecosystem conventions (and the associated quality differences)* (Walton, 2018)?

We can call a sharper form of this question the discrimination problem (Walton, 2018)—what quality of data and inference is required to discriminate reliably between alternatives that lead to significantly different actions and outcomes? For individual AI components this translates into an analysis of the risk and tolerance associated with false-positives and false negatives. *But when AI components rely on*

different data and ecosystem conventions, under what circumstances can organisations integrate them to enable successful discrimination? And under what circumstances will ML be sufficient and when will it need to be supported by causal reasoning or simulation (Pearl and MacKenzie, 2018)?

For many business challenges—the management of compliance regulations is an obvious example—rationale is important; the reason for an answer is as important as the answer itself. But deep learning does not support this well even in the case of single AI components (although work is underway (Foy, 2018)). *In the case of multiple AI components, how can an organisation overcome this transparency challenge?*

This is one example of a deeper underlying problem, that of ecosystem boundaries. One type of ecosystem boundary, between AI and humans, is especially important (Fry, 2018). As AI tackles more complex topics the ability to exchange complex information successfully between AI components and people will become ever more important, leading to the question: *how can an organisation ensure that AI and people can work together successfully?*

The potential biases associated with AI are well known (DeBrusk, 2018). They highlight a wider question: *how can an organisation assure the outcome of integrated AI components against a range of organisational requirements, not just for individual interactions but over multiple interactions?*

These questions introduce the first two levels of fitness. The concept of fitness within an ecosystem (which measures how well an information processing entity fits its environment (Ford, 2017; Walton, 2018)) breaks down into three levels:

1. narrow fitness: the ability to achieve favourable outcomes in a single interaction;
2. broad fitness: the ability to achieve favourable outcomes over multiple interactions, potentially of different types (this is the level that reveals bias and, more generally, ethical and social issues);
3. adaptiveness: the ability to achieve favourable outcomes when the environment (determined by the frequency and nature of interactions) changes.

Note that there is a tension between these—an excessive focus on one can diminish the ability to achieve the others.

Organisations have a set of internal selection pressures (created from budget processes, culture, performance management, organisation design and others) that are supposed to make the organisation fit for its environment. But they do not always align well with each other or the environment. In an era of disruption, especially, organisations need internal selection pressures with a different balance between the levels of fitness. For example, the difficulty that organisations have with transformation (Capgemini Report, 2018a) shows that organisations may have insufficient internal selection pressures to support adaptiveness (often resulting in high levels of friction associated with change) and consequently struggle to keep pace with changes in their environment.

Current business pressures relate directly to this—the need for greater organisational responsiveness (Capgemini Report, 2018a) means that adaptiveness is more important than before. In addition, the digital and AI revolution means that end-to-end information quality (Westerman et al. 2014) is increasingly important.

Since machine learning is about learning, this, in itself, poses a question: *how can an organisation use AI/ML to learn about changes in its environment and then make the required changes quickly and reliably (Walton, 2018)?*

Opportunities

The opportunities for AI are legion. As the authors say, with respect to AI, in (Capgemini Report, 2018b): “Almost any existing or new application can deliver more value by augmenting it with a touch of ‘smart.’” We can think of the opportunities in a number of categories:

- *The organisational environment*: making sense of the torrent of data available to understand opportunities (customer needs, attitudes and preferences, their specific and increasingly real-time context) and threats (including security threats, reputational threats and fraud) and take appropriate action;
- *Operations*: making sense of the data from operations, partners and the supply chain to understand status, predict and manage incidents and failure and improve efficiency and reliability;
- *Interaction*: using the capabilities of natural language processing and other sensing capabilities to interact with people (including employees, service users and customers);
- *Case management automation*: understanding what cases can be routinely automated and what cases need specialist intervention (and when);
- *Governance*: improving the quality of information available to support (automated or human) decisions (Kahneman points out (Kahneman, 2011) that, without conscious intervention, people are “radically insensitive to both the quality and quantity of information that gives rise to impressions and intuitions”);
- *Adaptiveness*: helping an organisation to improve its response to changes in the environment by, for example, re-learning business rules.

More generally, AI can help organisations to develop both operational and strategic situation awareness and the ability to link that awareness through to action increasingly quickly, efficiently and effectively.

Research Agenda

The following paragraphs itemise a set of research questions relating to the challenges and opportunities outlined above.

- *Data*: how should organisations structure their business and technology architectures to support data engineering (and its links with IoT, digital twins and other technology trends) and data governance to support multiple AI components with different ecosystem conventions? How can they ensure that the quality of the data is sufficient to support the required analysis?
- *Discrimination*: under what circumstances and to what extent can organisations rely sufficiently on the discrimination provided by sets of integrated AI components based on different data and ecosystem conventions?
- *Assurance*: what capabilities, controls and mechanisms do organisations need to put in place to understand and assure sufficiently the risks (for each level of fitness) associated with implementing single, multiple and integrated AI components?
- *Transparency*: under what circumstances do organisations require transparency of reasoning and how can this be delivered when AI components are integrated?
- *Adaptiveness*: how can AI contribute to improving the adaptiveness of organisations and how can organisations derive the right balance between the different levels of fitness using AI components?
- *Working together*: how can AI be designed so that complex information can be exchanged reliably between AI and humans—how can they work together effectively?
- *Internal selection pressures*: how can AI support the development of internal selection pressures that can support the right balance between the different levels of fitness?
- *Inference approach*: for which business use cases will ML be sufficient (assuming availability of the right data) and for which will it need to be supported by different forms of causal reasoning or simulation?

3.2. *Business and Management Perspective*

3.2.1. **A Decision-Making Perspective - Yanqing Duan, John S. Edwards, Yogesh K Dwivedi**

Challenges

The earliest development of AI was the construction of an intelligent machine that could mimic human decision making for playing chess. Since then, using AI in decision making has been one of the most important applications in AI history. The roles of AI in decision making have been classified in various ways. Broadly speaking, AI systems can be used either to support/assist the human decision makers, or to replace them (Edwards, Duan, & Robins, 2000). More specifically, the early publication by Bader, Edwards, Harris-Jones, and Hannaford (1988) identified six roles for knowledge based systems: Assistant, critic, second opinion, expert consultant, tutor, and automaton. As the current advancement in AI technology enables researchers to create more advanced machines, it is possible for AI to undertake more complex tasks that require cognitive capabilities which previously seemed impossible, such as making tacit judgements, sensing emotion and driving processes (Mahroof, 2019). As a result, an increasing number of jobs are autonomously performed by AI systems without human control and supervision (Zlotowski, Yogeeswaran, & Bartneck, 2017). There are many reports on the benefits of AI for decision making because AI is believed to be able to reach better decisions, to boost our analytical skills and decision-making abilities, and heighten creativity (Wilson & Daugherty, 2018). However, “with the resurgence of AI, a new human-machine symbiosis is on the horizon and a question remains: How can humans and new artificial intelligences be complementary in organizational decision making?” (Jarrahi, 2018 p. 579). Miller (2018) argues the imperative of a new human-machine symbiosis and calls for the rethink of “how humans and machines need to work symbiotically to augment and enhance each other’s capabilities.” (page 2). For example, what would be the implications of using AI for future business executives in making strategic decisions?

Opportunities and research agenda

To advance our knowledge and understanding on the new generation of AI systems for decision making, Duan, Edwards, and Dwivedi (2019) propose twelve research propositions in terms of conceptual and theoretical development, AI technology-human interaction, and AI implementation. Based on Duan et al. (2019)’s comprehensive review and discussion, this section provides the following specific research areas on the emerging challenges and research agenda of AI from a decision making perspective.

- (a) Theorising the use of AI and its impact on decision making: *It is necessary to theorise the use of AI and its impact on decision making. Therefore, an integrated conceptual framework is needed to provide a systematic understanding of AI in decision making.*

With the rapid increase in AI applications, many claims are made by AI developers and large corporates about its use and substantial benefits and impact. For example, according to Davenport and Ronanki (2018), a survey of 250 executives who are familiar with their companies’ use of cognitive technology (a term Davenport and Ronanki explain as “next-generation AI”) shows that three-quarters of them “believe that AI will substantially transform their companies within three years” (p.110). As most similar claims are not substantiated by measurable empirical evidence and rigorous academic research, it is difficult to know how, why and to what extent AI systems are being used and impacting on individual and organisational decision-making performance and transforming organisations. This raises an opportunity for IS researchers to develop appropriate theoretical justifications on the use and impact of AI for decision making through the appropriate theoretical lens.

- (b) Re-defining the role of AI for decision making: *AI can play multiple roles in decision making, but there are contradictory views in the current debate on the role of the new generation AI. Will AI be mostly accepted by human decision makers as a decision support/augmentation tool rather than as the automation of decision making to replace them?*

Many previous studies have examined the roles of AI before the era of Big data. However, considering the super power of the new generation AI and the overwhelmingly mixed views and debate on the new role of AI in decision making, it is imperative that the role of AI should be revisited and redefined.

Some argue that AI should be used to augment the human judgement rather than automation (Miller, 2018; Wilson & Daugherty, 2018) and “AI systems should be designed with the intention of augmenting, not replacing, human contributions” (Jarrahi, 2018 p. 584), but this assertion should be further supported with rigorous research and investigation with empirical evidence on how and why AI is best at providing augmentation in supporting human judgement rather than decision automation. Wilson and Daugherty (2018) argue that companies that deploy AI mainly to displace employees will see only short-term productivity gains. What is the evidence for this claim? If this is true, why and how will using AI for replacing employees not deliver the long term gains and how can this shortcoming be overcome?

- (c) Measuring the impact of AI on decision making performance: *Measuring the benefit of AI and its impact can be very difficult, but possible. There is a need to develop and test theoretically sound and practically feasible AI impact indicators to measure its benefits.*

To address this issue, researchers need to clearly understand the role of AI in decision making process. For example, if it is in a decision support role, what is the most appropriate way to measure the AI's impact on the human decision makers' performance? Wilson and Daugherty (2018) claim that companies can benefit from optimizing “collaboration between humans and artificial intelligence” and develop employees' “fusion skills” that enable them to work effectively at the human-machine interface, but how can these benefits be directly measured?

- (d) *Developing and testing System design criteria for supporting decision making:* The ergonomic design of AI systems is important for their success, but the ergonomic issues are different between supporting, augmenting, replacing, or automating systems.

As the effectiveness of AI systems for decision making can only be realised through its acceptance and use by the end users (Edwards et al., 2000), the system design criteria for AI based systems has been an issue since the early applications of AI. Based on our understanding of the roles of AI, whether for supporting, augmenting, replacing, or automating decision making, IS researchers need to propose the design criteria from technology-human interaction perspective for system developers to create ideal AI systems for human decision makers. For example, what are the ergonomic design issues for developing AI systems that are suitable for decision making?

- (e) Refining and improving AI system performance while in use by decision makers: *Can AI systems performance for decision making be refined and improved by deep learning while the systems are in use by decision makers?*

The unique strength of human intelligence is its ability to learn and adapt to new environment and challenges. Refining and improving performance through continuing learning has been a challenge for advancing AI until the recent advances in deep learning and Big data. Deep learning, as a subset of machining learning, has been one of the essential enablers for the renewed AI success. Can AI systems be refined and improved by deep learning while they are in use by decision makers? This question needs to be addressed by further research.

- (f) *Understanding the critical factors affecting AI's success in decision making:* There is a need to identify the critical factors that will significantly affect AI's success for decision making.

While technology advancement may have no limit, its applications may encounter bottlenecks and unprecedented barriers. Factors affecting the use, impact, success and failure of information systems have been studied extensively (Dwivedi et al. 2015; 2017ab; Hughes et al. 2016; 2017; 2019). There has been some work on critical success factors for implementing data mining systems (Bole, Popovič, Žabkar, Papa, & Jaklič, 2015), but across the board there is a lack of research on identifying the critical success factors affecting the current use of AI and its impact in the era of Big data.

- (g) Understanding the relationship between culture and the use of AI in decision making: *The acceptance of AI for decision making can be affected by different cultures and personal values. On the other hand, the acceptance and successful application of AI for decision making may result in a change of culture in organisations and in individual decision-making behaviour.*

Culture has been recognised as an important influential factor in technology acceptance by many studies in the past. Does culture, such as national or organisational culture, and personal and religious values,

also play a critical role in acceptance/adoption and use of AI applications? For example, Gerbert, Reeves, Ransbotham, Kiron, and Spira (2018) examine “Why Chinese companies approach AI differently”. Liu, Chan, Zhao, and Liu (published online 2018) also find a significant influence of both organisational and Chinese national culture on knowledge management. If culture does play a role, how, why and to what extent does it affect the AI success? Will the wide use of AI for supporting and automating human decision-making change culture? This is an area that has not been well explored so far, thus requiring further investigation.

3.2.2. AI-enabled Automation - Crispin Coombs

Challenges

Advances in Artificial Intelligence (AI) technologies have seen a step change over the last 10 years. One consequence of these developments is the creation of new opportunities to automate existing work tasks. Automation can be defined as the execution by machine, usually a computer, of a function previously carried out by a human (Parasuraman and Riley 1997). AI-enabled automation technologies can manage and analyse vast amounts of data, propose recommended courses of action and enact these decisions. These technologies are also able to improve their decision accuracy over time, thereby becoming increasingly more valuable to organizations (Tarafdar, Beath and Ross, 2017). Such ‘intelligent’ capabilities have enabled AI to be applied in repetitive and routine knowledge work, such as improving stock market timing and portfolio creation (Hilovská and Koncz, 2012) or identifying firms that are at most risk of bankruptcy (Chaudhuri and De, 2011). While much of the recent rhetoric assumes full automation of job roles (e.g. Frey and Osborne, 2017) a notable feature of many AI applications is the continuing need for a human to work alongside the automation technology. Human workers are needed to either assess and confirm AI decision recommendations, enact the AI recommended course of action, or provide backup support should the AI-enabled automation produce errors or fail. This has led scholars to argue that AI-enabled automation will augment the work of humans, rather than enable wholesale substitution (Davenport and Kirby, 2016). Thus, understanding how humans work alongside AI-enabled automation will be critical to deliver the anticipated benefits of automation.

The Human Factors, Ergonomics and Safety Engineering literature has an established stream of research that examines the impact of traditional automation technologies on human workers. This literature provides an important starting point for Information Systems scholars wishing to investigate these issues (Markus, 2017). This literature suggests that to maximise the benefits of AI-enabled automation, organizational decision makers are likely to be faced with four major challenges: i) how to select tasks for automation; ii) how to select the level of automation for each task; iii) how to manage the impact of AI-enabled automation on human performance; and iv) how to manage AI-enabled automation errors. Each of these challenges is briefly discussed below.

First, when considering tasks for AI-enabled automation organizational decision makers need to recognize that work tasks can be sub-divided into specific stages. For example, information processing tasks comprise of (1) information acquisition; (2) information analysis; (3) decision and action selection; and (4) action implementation (Parasuraman and Wickens, 2008). AI-enabled automation may be applied to each individual stage or across all stages. Thus, organizational decision makers need to consider whether AI-enabled automation can be applied to all the functional stages of a work task and whether this is desirable for the business process.

Second, organizational decision makers need to appreciate that each work task stage may have a different level of automation applied. The level of automation may range from Level 1, manual control where the computer offers no assistance to Level 8, autonomous control stage where the computer does everything without human notification (Vagia, Transeth and Fjerdingen, 2016). Thus, as well as selecting the appropriate work task stage to automate, organizational decision makers also need to decide how much decision-making control is given to the AI-enabled automation, and to what extent a human is kept in the loop.

Third, the level of automation selected for functional task stages may have impacts on human worker performance. These impacts may be positive or negative. For example, higher levels of automation may reduce operators' workload and achieve better results. However, higher levels of automation may also reduce the situation awareness of the worker, and increase a tendency to overly rely on automation technology (Onnasch et al., 2014). Thus, organizational decision makers need to understand the factors that may influence human worker performance when working alongside AI-enabled automation.

Fourth, even the most reliable technological systems are likely to fail or err at some point and when this occurs, humans must engage in error management. Highly automated systems that do not require frequent intervention are hard for humans to keep attention to (Parasuraman and Manzey, 2010). This creates an automation paradox, where factors that positively influence performance when the automation is working well may undermine performance when the automation errs or fails (Onnasch et al., 2014). Leaving the human out of the loop can be problematic because it leads to considerable human performance impairment if the automation suddenly fails. Thus, organizational decision makers need to understand how AI-enabled automation errors or failures can be managed. These four challenges present several opportunities for Information Systems scholars.

Opportunities

There has been considerable research that has examined the types of automation that may be applied to different tasks and stages of tasks (Parasuraman, Sheridan and Wickens, 2000; Sheridan and Parasuraman, 2005; McBride, Rogers and Fisk, 2014). These studies reveal that adopting strategies of automating tasks that machines do best and leaving the residual tasks to human workers is likely to have negative impacts on performance (Parasuraman, 1997). To help decision makers develop more sophisticated automation strategies several quantitative and qualitative models have been developed (Parasuraman, 2000). While these models provide a valuable starting point, further research is needed to explore how quantitative and qualitative models may be combined to provide richer insights regarding appropriate and desirable AI-enabled automation of tasks.

The literature also indicates that selecting appropriate levels of automation is a complex process that is highly contingent on a wide range of factors (Parasuraman, 1997). The level of automation selected may be dependent on person factors (e.g. the complacency potential of the human operator, the automation training provided, and the knowledge of automation held by the worker), task factors (e.g. the consequence of automation error, the cost of verification, and lines of accountability), or cognitive load factors (e.g. associated impacts of automation on mental workload or situation awareness) (McBride, Rogers and Fisk, 2014). Thus, broad recommendations of 'medium' automation adoption levels are likely to be unhelpful as they do not take sufficient account of these important contingencies (Onnasch et al., 2014). Given the capabilities of current and projected AI-enabled automation technologies, more empirical research is needed to examine the conditions that influence the level of automation applied to task stages.

Existing research has shown that when working with automation technologies human performance may be influenced by automation complacency and automation bias. Automation complacency is defined as the poorer detection of system malfunctions under automation compared with under manual control (Parasuraman and Manzey, 2010). For example, human operators (e.g. pilots, air traffic controllers) not conducting enough checks of system state and assuming "all is well" when in fact a dangerous condition is developing that leads to an accident. Automation bias has been defined as people using the outcome of a decision aid as a heuristic replacement for vigilant information seeking and processing (Mosier and Skitka, 1996). It may occur because the automatically generated cues are often very salient and draw the human's attention and because humans tend to ascribe greater power and authority to automated aids than to other sources of advice. Although, automation complacency and bias can speed up decision making when recommendations are correct, when the automation technology provides the incorrect recommendations it can lead to omission errors (the human does not respond to a critical situation) and commission errors (the human follows the recommendation of the automation, even though it is incorrect) (Parasuraman and Manzey, 2010; McBride, Rogers and Fisk, 2014). This presents an important research opportunity to explore and understand the factors that influence over reliance on

automation and how to counter them, especially if the human is retained as the backup to AI-enabled automation.

The management of automation errors may also be influenced by automation complacency and automation bias. Automation complacency among human operators increases with higher levels of automation and higher automation reliability (McBride, Rogers and Fisk, 2014). This increase is because human workers are less aware of changes in the environment or states when the change is made by an agent other than themselves (human or automation). The risk of negative consequences associated with AI-enabled automation errors or failure increases with increasing levels of automation and in the latter functional stages of information processing (Sebok and Wickens, 2017). Thus, further research is needed to investigate features that can mitigate the loss in performance, in circumstances of error or failure, with higher degrees of AI-enabled automation.

Research Agenda

In order to address these research challenges and opportunities for understanding how humans work alongside AI-enabled automation several research priorities are proposed.

First, further empirical research is needed to investigate how are decisions made regarding the work task to automate and level of AI-enabled automation to apply. As automation becomes increasingly intelligent through the application of AI the range and types of task that it may apply to are likely to grow. Although qualitative and quantitative models have been developed to conceptualize this decision-making process, they have been developed from studies that examine traditional automation technologies and adopt a functional task perspective. Although these studies help to explain how existing tasks or activities may be automated, they may not adequately explore new ways of undertaking business processes or the development of radical new business models. Thus, further research is needed to investigate how strategic applications of AI-enabled automation may redesign or create new business processes and how the role of the human worker may evolve alongside these developments, the new job roles that may be created and the skills required to undertake these roles. These studies should combine qualitative and quantitative models of automation selection and account for contingency factors such as person characteristics, task characteristics and the associated cognitive factors that may influence the level of automation applied.

A second research priority is to understand the factors that may influence human over reliance on AI-enabled automation and how they can be countered. As AI-enabled automation becomes common and reliable there is an increasing risk that humans will privilege AI recommendations and decisions over their own judgements and suffer from reduced situation awareness. While reduced situation awareness has critical implications in transport and health contexts, poor situation awareness may also bring significant risks in many business and management settings, such as imperfect AI-enabled automated decisions leading to stock market crashes or firm bankruptcy. Research that studies the auditory and visual cuing of automated system performance, as opposed to relying on alerts when errors occur, or the system fails, would be valuable to address this research priority (Hancock et al., 2013). Research could also explore how AI could be used to design ‘likely’ alarms (Parasuraman, 1997) rather than relying on alarms to be definite warnings of dangerous situations, or apply adaptive automation that can vary the level of automation applied in real time (Hancock et al., 2013) to help to reduce loss of situation awareness due to out-of-the-loop unfamiliarity.

A third, related research priority concerns the use of human workers in failsafe capacities to protect against AI-enabled automation error or failure. Human workers are likely to find it difficult to undertake this failsafe role effectively in situations of high AI-enabled automation reliability and when they have few opportunities to practice performing the task. Thus, further research is needed to investigate how human workers can be trained and supported to continue to be able to effectively monitor and respond to AI-enabled automation errors and failures. For example, research could investigate how human workers can be trained to “expect the unexpected” as well as training in understanding of AI-enabled automation logic. Further, as higher levels of automation become more pervasive, AI-enabled automation will become more challenging to manage in situations of automation error or failure. Thus, further research is needed to explore how AI-enabled automated decision making can be made

sufficiently transparent for a human to diagnose error creating faults. This is a critical research priority because understanding 'what happens when it goes wrong' is a key factor for organizations wishing to increase their level of automated decision making.

Information Systems scholars have a critical role to play in shaping the agenda of how AI is applied in organizations and society in the future. It is hoped that this research agenda will be useful to scholars and contribute to a better understanding of how AI-enabled automation may deliver positive benefits to society.

3.2.3. Labour under partial and complete automation - Spyros Samothrakis

One of the most stunning facts in the history of labour is the universality of the belief that automation is going to reduce aggregate labour hours. On the more "progressive" side, thinkers from the whole of the political spectrum, including Keynes (Keynes, 1930), Nixon (Blair, 1956) and Stalin (Stalin, 1952) were adamant that through a combination of policy and technological automation, we would see a drastic reduction of working hours. For those with a more pessimistic bend, more automation meant more unemployment; the beginning of this idea probably goes back to the luddites (David, 2015), who actively tried to remove machines from the production process as a means to preserve jobs. This belief (as part of a generalised fear of technological unemployment) has been re-iterated multiple times.

Unemployment and/or lower working hours never materialised. Unemployment seems to follow cyclical business patterns, with almost no scholar making a case for technological causes. This does not mean that certain professions will not disappear (Frey and Osborne, 2013), but that economy is on a permanent reconfiguration state. Working hours on the other hand did gradually decrease until the 1970's; from that point onwards working hours have either stayed stable or increased (especially in the US), while extreme working hours have increased everywhere (Burger 2015). The contradiction here is apparent - technological development has been astounding for the last 40 years, but the need for labour has not diminished.

Outcomes after the limit case

If we are to take the idea of work automation to its limits (but on the same time assuming that through control or technological inability, god-like AIs never materialise), humanity's ability to produce might only be constrained by the availability of raw resources; human labour will no longer be needed to supplement machine labour. In this scenario machines become non-conscious slaves, with no further human involvement in production, even at planning or at discovery level. How close is this idealised limit to a possible real limit will play a crucial role in future societal developments, in conjunction with societal organisation. The idea of a humanity not needed for production has been maintained in various publications (e.g. Joy, 2000), but a thorough discussion is provided in Frase (2016). The argument is simple - if technological trends are to reach their limit, we can discern four possible futures; a) *Communism*, as a combination of abundance and equality. b) *Rentism* the idea that abundance combined with restricted access to goods (i.e. imposing artificial restrictions akin to copyright protections on music distribution). If we are to assume that technological progress cannot fully automate production, or, due to inherent limits, one cannot reach over-capacity in almost everything, a future with widespread equality would be called *Socialism*. The worst case scenario, termed *Exterminism*, projects a highly unequal future combined with scarcity, where the vast swaths of humanity being are condemned to irrelevance and base their reproduction by being servile to tiny fraction confined in reverse ghettos.

Trajectories towards the limit case

Automation of the level described in the previous paragraph seems to be far away - or at least not imminent. Technologies that originally seemed trivial and around the corner (e.g. self-driving cars, see Brooks, 2019) are now thought of as requiring years of further development. At this moment, AI seems to be automating jobs that were traditionally thought of as middle management; it also plays a role in intensifying labour. Examples include Uber's allocation algorithms and Amazon's hand gesture patents. The core of the issues lies with worker performance management increasingly delegated to machines (De Stefano, 2018), creating dystopia like conditions for the ones affected. It is hard to see how a full-automation (or almost full automation) society will not be impacted by the technological trajectory that led to it. It's also hard not to wonder when will this almost teleological point in history arrive. There

seem to be wide disagreement among scholars and experts, but most seem to agree we would have achieved full automation within 100 years (Müller and Bostrom, 2016; Walsh, 2018). If the current trends persist, the trajectory towards the AI limit case will be painful for most.

What is missing?

The focus on management, surveillance and other labour disciplining technologies is not necessarily out of choice. We are bad at creating machines that act in unconstrained environments; our AI systems traditionally need copious amounts of data and tend to produce dubious results outside well defined conditions. They are also not very good at learning the invariances of this world, and fail to generalise outside their training distribution. This constraints practitioners into solving problems that can be attacked fast, which are almost always high level optimisation problems. Tasks like mending a broken car away from a production line, basic plumbing etc. are completely outside the capabilities of modern AI. The current crop of AI also fails miserably to learn incrementally from data - something termed "catastrophic forgetting". One can only speculate what an AI for Good would imply, but my best guess is an always-on private advisor and personal guide. Efforts to develop similar technologies in the networking arena are late (see Moglen, 2013; Bielenberg et al., 2012), but have managed to gather significant traction - maybe there is room for an AI equivalent?

3.2.4. A Generic Perspective – Arpan Kar

Challenges

The growing popularity of AI is changing the way firms are engaged in doing business across industries. The benefits and productivity improvement at the tactical, operational and strategic level are envisaged to be huge as the firms move towards digital transformation empowered with AI. The information assets residing in these firms, often referred to as big data, are systematically exploited and explored by AI to create this value (Grover and Kar, 2017). Similar value is also realised in government, public organizations and not for profit organizations. However, there are major challenges remaining in this journey to explore and exploit the full potential of AI. In our limited perspectives, these can be segregated in terms of algorithm specific challenges, domain specific challenges and policy related challenges.

First, let me try to explain the algorithm specific challenges. Reviews of artificial intelligence algorithms (Chakraborty and Kar, 2016; Kar, 2016; Chakraborty and Kar, 2016) have demonstrated that most of these applications are focused on showcasing usage of relatively few approaches. Probably eighty percent or more of the published literature is covered by algorithms like neural networks, random forest and decision trees. To an extent some work has been published on algorithms like genetic algorithms and swarm intelligence. While around 2010, there was a new focus on developing new AI algorithms due to computational limitations of these age old algorithms, the focus has relatively died down with the growing popularity of deep and convoluted neural networks. This trend is predominantly driven by the growing access to high performance computing infrastructure in academic and industrial research units. Hence the focus on exploring newer algorithms for theory development has taken a back step as researchers are focusing on exploiting these established algorithms in the wake of improved computational infrastructure. So theory development in many niche algorithms has received less priority, as compared to what it should receive. This creates a gap in the long process of knowledge development in the domain, as current users continue to exploit well known algorithms with better computational platforms while exploration takes a backseat in this journey.

Next comes the domain specific challenges. The focus on exploiting AI inherently means that organizations have to systematically develop and maintain information assets, which requires a digital transformation within these organizations. However, in many of these organizations, when the initial planning is being done, there is a gap between digitalization and digital transformation, due to the organization's overall technology readiness. Therefore there is a challenge on identifying the right questions, what data needs to be captured to answer these questions, understanding approaches to extract, maintain and analyse these data and understanding the implications of this analysis. This journey essentially means that there has to be professionals who can understand both the functional

elements of the organization's processes as well as appreciate the technical elements of AI. This is often missing in existing organization as they gear towards taking a big leap to leverage AI, and thus sometimes, due to the lack of internal readiness, there is a productivity paradox that emerges due to lags in learning (Barton and Court, 2012). So AI usage needs to have greater adoption before it affects the industry productivity as a whole.

Further there are challenges of estimating trade-offs between differentiation versus commoditization of AI. Like any information technology, the economic returns of AI is most high when it reaches a maturity of commoditization. But AI systems are also expected to evolve themselves as they learn from the contextual and sticky knowledge within organizations, which mean that outcome of AI can never truly be commoditised. However current maturity of digital transformation journey across organizations, even within the same domain, does not facilitate too much of commoditization.

Since it is a relatively new hype in terms of applications, although the technologies are old by quite a few decades, the actual readiness of the organizations producing or consuming the service enabled through AI, is often less understood. Process maturity and people maturity in such organizations become questionable. As a result, issues surrounding how these information assets are developed, maintained and exploited, becomes debatable, when adverse impacts are witnessed. Challenges of privacy preservation, security and process alignment becomes critical. Further people who will use these technologies need to undertake severe reskilling and deskilling.

On the policy side, similarly there is a lack of mature standards and public policy to address these challenges. What could be measures of intervention from government to control market concentration? The organizations which are the market leaders in the segment have many customers onboarded, and as a result have the requisite data created in their platforms which is exploited by AI, to provide differentiating services. A small firm will be less effective purely due to lack of access to the data. However, this brings in a possibility of an AI divide where strong research units continue to grow and reap benefits while other smaller units fail to take their innovation to the next level. However, there are procedural challenges in the decentralization of innovation in AI and policy to govern this.

Opportunities

The opportunities in AI are tremendous given that it is still at a rather nascent stage in terms of adoption in different industries. So it would be exciting for industries to explore different slices of AI impacts in different contexts. Such opportunities of theory development for researchers in AI could come from exploration in the following themes.

- Challenges and issues in managing AI in organizational and social setup.
- Impacts of AI on organization design and associated issues
- Impacts on behaviour of individual stakeholders who are affected by AI and the cycle of how they affect the outcome of AI
- Requirements surrounding deskilling and reskilling human workforce in the wake of AI usage in Industry 4.0
- AI impacts from a systems methodology – drivers and actors of the ecosystem

Also it would be interesting to explore opportunities of how AI can be leveraged not only in the firm level but as an enabler in platforms and ecosystems. AI may help to connect multiple firms and help in automating and managing information flows across multiple organizations in such platforms. It would be good to explore opportunities for AI to be used in such platforms to impact platform productivity, firm productivity, and ecosystem productivity.

Further research in AI from a technical perspective would also have immense opportunities in the years to come.

- Areas could be related to computational algorithms for making sense out of unstructured and large volumes of data
- Exploration could be in non-deterministic polynomial-time hard problems even with structured data but high volumes

- It would also be interesting to explore the role of AI in conjunction with decision theories for management.

Research Agenda

Building blocks for future research in AI can stem from integrating classic information systems research theories emerging from management theory, organization theory, behavioral theory, computer science theories and systems theory (Barki, Rivard and Talbot, 1993). This should be done by extending the exploration in computer science for contextual applications in organizations, markets and society. A particular area of interest would be the role of AI in networks consisting of different actors and types of linkages. Currently most of the research in AI is happening in computer science and information technology departments in universities. Such computational work is mostly getting presented in leading computer science conferences like Neural Information Processing Systems, International Conference on Machine Learning, Association for the Advancement of Artificial Intelligence and other such technical conferences. However the focus of such conferences is mostly addressing the computing block of information systems. Connecting such studies and progresses with management, organization, behavioural and systems theories in information systems would allow exploration of multiple complex phenomenon of AI in this journey towards digital transformation. In particular, this may lead to very strong contribution for policy making and practice, based on such mixed research methods.

However there is also a strong need to relook at theory and relationships based on the emergence of AI. The nature of data available due to digital transformation is completely changing the traditional approaches of research. The presence of big data on platforms like shared economy, social media and internet of things, may require a different approach of theorising than from the traditional research methodologies (experiments, surveys and interviews). This journey would also require researchers design research methodologies from studies connecting both positivist and interpretive paradigms. For theory development, proxies of constructs may be derived from big data which is getting generated in different data sources. For example, relationships between such constructs may require both qualitative and econometric validation, and since the data has high veracity, new acceptable levels of statistical thresholds may require to be adopted for theory development. So there may be a perceived trade-off between rigour versus the generalizability and applicability of such findings if one were to evaluate such research purely from a reviewing perspective. However, given that the area is still nascent, it would be good overlook the minor rigour-relevance gaps and try to take forward some of the new insights in AI and their impacts on the ecosystem they serve.

3.2.5. Artificial Intelligence for Digital Marketing - Emmanuel Mogaji

The vast amount of data being generated, increased use of mobile device, cloud computing and internet has contributed to the significant development of Artificial Intelligence (AI). AI is making a double-edged impact - constituting a significant source of innovation yet threatening human jobs (Huang & Rust, 2018), this piece, however, focuses explicitly on discussing the opportunities of AI for digital marketing. Wirth (2018) noted that the industry seems hesitant and at the same time eager to embrace this new technology. This piece will explore some of the challenges for its adoption and research agenda for a better understanding.

Opportunities

Artificial intelligence offers opportunities to enhances campaign creation, planning, targeting, planning, and evaluation. Three key stakeholders are identified as the opportunities for AI in digital marketing are being explored. Firstly, the brands who need to understand their customers and communicate with them on a very personal and emotional level. Secondly, the Advertisers and Marketing agencies who are responsible for digital marketing strategies. They need AI to bridge the gap between the brands, the customers and data (Bell, 2019) and Thirdly, the customers who need to engage with the brands' marketing communications. They are the recipient of the information and the generator of the data which is being used to targeting. With this understanding, the opportunities for these stakeholders are presented, especially for digital marketers.

Data: A large amount of data generated by the consumers provides an insight into their behaviour. Customer analytics makes up 48% of big data use in sales and marketing (Columbus, 2016) which highlight there are new sources of data about the customers. Advertisers have seized the opportunity to use this data to personalise and target advertisements (Boerman, et al., 2017). Marketers have never had this form of data from the customers. No doubt these are big data collected over different touch points. However, AI offers the opportunity to process these data faster and effectively engage with everyone with messages that appeals to them. Segmentation and targeting become very easy through the data available.

Content Creation: With AI being able to do what humans will typically do, there are opportunities for more innovated and relevant content creation. With consumers' demand for relevant content, advertisers can explore the prospects of AI to develop contents relevant to the customers because they now have a better understanding through the analysed data. Content here includes advertisement, social media posts and email campaigns. Information such as past purchases, interests and browsing behaviours can be used to create automated campaigns that can enhance the customers' purchase intention. AI can identify the consumer's pattern about lifestyle choices including music, favourite celebrity and location to create unique content.

Content Sharing: With the understanding of the customers and the creation of relevant content, AI can also go further to deliver these messages to the customers in a non-intrusive manner. With customers engagement and information collected such as location, demographics, devices, interaction with the site, AI can display offers and content that are more appropriate for each user type. Analysed information about the customers determine the best times and days of the week to send an email campaign or post on social media, the recommended frequency of the marketing messages and the title they are more likely to engage with. This content sharing opportunity builds on the power of Programmatic which allows automated bidding on advertising inventory in real time.

Challenges

Despite these opportunities, some challenges may hinder the adoption and implementation of AI for digital marketing.

The Availability of Data: There are challenges for collecting and using the data, especially considering The European Union General Data Protection Regulation (GDPR). Data is essential in understanding the customers, their journeys and developing the advertising campaigns. Personalised and automated content creation and sharing will not be possible if the data are not available. When customers are not willing to release relevant information, the AI algorithm is not receiving the needed resources to learn and develop the process. The AI algorithms need access to that data to give accurate recommendations. Even when the data is available, it should be AI ready, that is it is readily available for machine learning. Companies have been collecting information about their customers for many years, and it is essential that they start considering the information with regards to AI, making it structured enough for digital marketers to use.

Resources: Though AI is getting much attention as a fast-developing technology, the cost needed to it for digital marketing may be a limiting factor. Top IT companies and Start-ups champion most of these developments; it will not be surprised if AI is just limited to some of the biggest advertising agencies who have the financial capabilities. The financial implication of research and development that goes into it creating and maintaining AI does not make it readily available for everyone but no doubt it will become cheaper as times goes on. Besides, human resources needed to champion these projects might also pose a challenge. The level of knowledge about AI in digital marketing is not keeping pace with the developing in AI as it becomes increasingly sophisticated. The insufficient level of skill individuals may be a barrier to exploring the full capabilities of data-driven digital marketing.

Trust in AI: There are trust issues with AI (Siau & Wang, 2018). Advertising practitioners are feeling that the machine is not creative enough or it is going to take their jobs, Brand feelings they are losing grip over their narratives, allowing the machine to generate contents and not convinced the algorithms can deliver results. Consumers are feeling; they are just being targeted. Knight (2017) suggested that there are dark secrets at the heart of AI because no one knows how the most advanced algorithms do

what they do and that could be a problem. Presenting the state of AI in 2019, Vincent (2019) asked if computers are not explicitly taught (as they learn on their own), how do you know how they make decisions, he further argued that teaching computers to learn for themselves is a brilliant shortcut. Moreover, like all shortcuts, it involves cutting corners. This inherent fear about the prospect of AI highlight challenges for its adoption for marketing communications.

Research Agenda

These opportunities and challenges open avenue for future research to understand how to best to harness the prospects of AI in digital marketing.

Conceptual and theoretical development: AI has been applied in many different domains such as medicine, hospitality and travel. While the possibilities of using artificial intelligence (AI) to extract information about customers, generate advertisements that will appeal to them and shared digitally has been presented, a holistic conceptual and theoretical understanding of these prospected is needed. The current hype around AI is creating a blurry picture calling for further research and clarification (Wirth, 2018). A systematic review of AI-related applications in digital marketing, definitions and terms with empirical insight is needed, especially within the context of the stakeholders – the advertisers, brands and consumers. Exploring how firms should integrate AI, either as human replacements or integration (Huang & Rust, 2018).

AI integration with OBA and MLBA: Following on the conceptual and theoretical development of AI in digital marketing, the integration with online behavioural advertising (OBA) and mobile location-based advertising (MLBA). Currently, behavioural targeting mostly occurs when using computers or smartphones (Gutierrez, et al., 2019), scholars argue that it offers personalized and targeted advertisement, offering a precise way of targeting customers (Kumar & Shaphali, 2016) and contributing to the growth in Online advertising revenues (Chen & Stallaert, 2014). Likewise, MLBA offers consumers benefits such as personalised communications that are tailored to the mobile user's real-time geographic location (Krishen, et al., 2017). These two concepts are emerging marketing strategies, and it involves collecting data either online or off-line and using it to develop advertising campaigns, With AI offering data collection and processing at a faster rate, a better understand and effort towards triangulating these online and offline data to have a better understanding of consumers' is essential. Providing practical implications for marketing researchers and practitioners.

Ethics: The ethical consideration between the personalisation of advertising and consumers' privacy represents the personalisation-privacy paradox (PPP) (Gutierrez, et al., 2019) often explored through the privacy calculus theory (PCT) (Xu, et al., 2011). Collecting, using, and sharing personal data for marketing purposed has always raised consumer privacy concerns (Boerman, et al., 2017), this concern is expected to grow has machines are being deployed to extract and process these data. A better understanding of how stakeholders deal with this concern is important. Consumers have misconceptions about extracting data for marketing purposes as they have little knowledge about it (Smit, et al., 2014) and yet advertisers and brands keep extracting these data. This is what Boerman, et al. (2017) described as 'information asymmetry' where companies know much about consumers, yet consumers know little about what happens to their data. Considering machine extracting these data without human intervention, a theoretical understanding of its implication is worth considering.

Content Creation: It will be necessary to intensify the exploration of the content creation capabilities of AI for digital marketing. This is an agenda marketing practitioner will find relevant, this follows the conclusion by Mogaji, et al., (2018) that personal data and information legitimately collected online by companies can be used to design and personalise advisements that appeals to consumers emotions and shared online. This process differs from the highly personalised and rational data such as age, gender, and location which Aguirre et al. (2015) found to have a reduced click-through rate but things that emotionally appeals to individuals like their choice of colours, images being used and background music. Harnessing data and expertise offered by AI to develop the marketing strategy offered a and enhance decision-making process, as Boerman, et al. (2017) **advised** that advertisers should consider the level of personalisation as advertisements perceived to be too personal can seem intrusive

Attitude towards AI developed Campaigns: There have been previous studies that uncovered some favourable and unfavourable consumer responses to ad personalisation, but the moderating factors that strengthen or weaken these effects are still mostly missing (Bleier & Eisenbeiss, 2015). Building on the previous study that explored consumer avoidance of personalised advertising (Baek & Morimoto, 2012), future research should endeavour to empirically explore factors that can influence the acceptance and avoidance of AI in digital marketing. Research should consider how well AI is targeting the customers with relevant advertisements as personalised advertisements increase intention to purchase when advertisement fits customers need (Van Doorn & Hoekstra, 2013). AI can extract the data and deliver the advertisement but how well are consumers engaging with it? What are they engaging with and what are they finding appealing. This information can help shape future development and ergonomic design of AI systems.

Stakeholders attitude towards AI for Digital marketing: Advertisers, consumers and brands attitude towards the innovation is also worth researching. As (Huang & Rust, 2018) noted, AI is taking over human jobs, come creative tasks are being threatened. How are professionally able to deal with these dynamics? How will marketers and advertising practitioners integrate AI into their job? Privacy concerns of consumers and trust in AI, transparency about the reason why companies and advertising agencies are collecting the data could be some deterrent to this initiative as Jai, et al., (2013) found that when consumers know that their information, collected on websites are shared with third-party companies, there is lower repurchase intentions, increased perceived risk and unfairness. Brands are aware of the financial implication and the benefit, how eager are they to explore the prospects of AI?

Metrics and Evaluation: The relationship between advertisement and intention to purchase should be revisited in the context of AI in digital marketing. Consumer awareness of personalised targeting through extracted data alter consumers' responses to online behavioural advertisements (Aguirre, et al., 2015). Also, Humans beings may be difficult to monitor and observed (Mogaji, et al., 2018). Their browsing history may not be a true reflection of their personality and what appeals to their emotions. Therefore, the metrics and form of evaluating the effectiveness of the AI developed campaign should be further explored. There is a need to develop and test the practically feasible of AI impact, its contribution towards the industry's growth, if it has increased sales for brands and if it has enhanced consumers choice making process.

Conclusion: While acknowledging the role and advancement of AI in everyday life, this piece has focused explicitly on the role of AI in digital marketing. The prospects, challenges and research agenda has been explored. AI offers enormous opportunities for key stakeholders. AI helps marketing agencies gets a better understanding of the data, to meet their goals and help brands connects emotionally to their customers. AI open opportunity for interdisciplinary collaboration involving AI developers and creative individuals, enhancing the power of AI to develop appealing advertising campaigns. Researchers following the research agenda provide theoretical insight and managerial implications relevant for AI developers, marketers and brand managers.

3.2.6. Artificial Intelligence for Sales - Kenneth & Leslie Caroline Le Meunier-FitzHugh

AI is changing the business landscape, and its effects are no less in Sales than in any other business function. Sales is where the business 'meets' the customer, whether it is in retail situations (business-to-consumer, B2C) or in business-to-business sales (B2B). Sales can take place face-to-face, through retail outlets, over the Internet or other communication media. Retail B2C shopping via platforms such as Amazon, is guided and influenced by various AI algorithms that have completely changed the retail selling experiences and this trend is set to continue for the foreseeable future. For example, recommendation algorithms present 'suitable' offers to on-line customers to consider, rather than waiting for the customer to make their selection. Additionally, a location algorithm will allow the customer to be presented with the location of outlets linked to their sales selections (Antonio, 2018). However, the impact of AI on sales generally goes much further than this. B2B sales are often more complex and have a greater monetary value per exchange than retail sales, although the latter are more numerous. The challenge for B2B sales is to understand how AI is influencing sales exchanges. The day has already come where salespeople may be prompted by AI in real time via their tablet or phone

during sales negotiations, in both B2B and B2C interactions. Further, some B2B sales functions are already being automated e.g. customer relationship software being used to identify sales readiness and telesales calls being initiated and guided by automated systems. It could be just a short step to AI providing integrative sales experiences on-line and through teleservices that could remove the need for salespeople altogether. The following section will explore some of the challenges and opportunities being offered by AI around the sales function, and then presents future possible research questions.

Emerging Challenges

AI is a job killer: Automation and automated services are replacing people in many industrial and service sectors to reduce costs and improve efficiencies. It is forecast that over 375 million jobs globally may be 'lost' to AI by 2030 (www.scientificworldinfo.com). The effectiveness of automation in sales has already been proven in telesales and forecasting situations, which have resulted in multiple sales-related job losses. It may be that as AI develops the mechanistic nature of the algorithms may reduce the need for competitive differentiation and creativity in sales exchanges. Additionally, as competitors use similar information derived from big data analytics to base their new product development (NPD) decisions on, or to develop 'customised' offers, it may become harder for customers to differentiate between offers and for salespeople to justify their existence. The proposition is that increased use of AI could reduce investment in sales training and development, increase monopoly/oligopoly situations and reduce the sales work available in that industry.

Loss of Privacy: The increased use of automated systems and AI opens up customers to privacy risks. While CRM systems allow companies to compare their customers' buying behaviours, the customers are at risk of finding this information in the public domain or being 'sold' to other interested parties. Salespeople may find that their customers are being 'poached' by other salespeople who have access to automatically-generated leads. Alternatively, salespeople may find that their previously personalised data that forms the bases of their customer relationships is now readily available to other parts of the company, reducing their effectiveness.

Changing the nature of salespeople's interactions with customers: The danger of the increasing use of AI allows B2B customer to self-select their sales deals, including pricing, discounts and special features, removing the need for human interaction. However, increasing our reliance on AI selling systems may result in Trust in the selling organisation being damaged. The increased use of AI removes the human touch and emotional connectivity that customers have developed with their sales representative. This loss of authenticity in the sales process may mean that buyers are unsure who to trust (Hurley, 2017). A further danger is that basing sales forecasting on past behaviours and on-line activities may perpetuate a bias, e.g. represent a past or random concern that is no longer relevant to the customer's current buying needs. While new types of customer insights may be created through AI, some of these may be too detailed or on the wrong track to be profitable. Finally, there is a danger of losing control of the sales process as integrated, automated systems prioritises emails, tracks new contacts and creates meetings or agendas of which the salesperson is unaware. This may lead to the salesperson no longer feeling in control of their activities and worrying about missing new opportunities that are not highlighted through the automated system (Loring, 2017), but which may have been identified by the salesperson in their interactions.

Lack of understanding of AI algorithms: It is sensible to pose the question, exactly what do sales algorithms do? Algorithms are meant to provide guidance and information to sales action by moving the customer along a prescribed route (Knight, 2017). They collect data on what the customer is looking at or is doing, and extrapolates the information that salespeople might require, which may be very helpful, or extremely annoying. The effects of algorithms still need to be researched further. If AI is driving market research, can the results be trusted? With the increase use of bots and auto-response algorithms, how can on-line market research be verified? The salesperson may be presented with inferior or bias information on which to base their sales negotiations.

Opportunities

Managing performance of salespeople: AI provides Sales Managers with dynamic assessments of performance via AI driven dashboards. They can be used to identify upselling and cross-selling opportunities to the company's customers. AI may also be used as a personal assistant that is able to schedule meetings with selected partners, releasing the salesperson's time for actually attending the meetings. An AI assistant can pull through prospective and existing customer data from internal files against key criteria or specified names (Loring, 2017).

AI predictive abilities in sales forecasting and customer management: Salespeople love up-to-date data continuously streamed to them wherever they are based. Customers like to be personally communicated with and AI can help salespeople to develop their relationships by providing this personalised information, saving time and preventing mis-directed sales efforts. Combining new algorithms with existing CRM platforms should allow for the analyses and prediction of selling opportunities, or the salesperson to identify changes in customer status (Antonio, 2018). The ability to leverage big data to focus the sales professional on their target customers, should enable building more authentic relationships. Additionally, scenarios and coaching may be provided by advanced behavioural analytics to produce suggestions of how to handle blockages in the sales process, and how to benchmark themselves against top performers (Hurley, 2017). An AI system can automatically update the CRM system through monitoring incoming and outgoing data. The predictive capabilities of AI can also now be used to gauge the customer's possible lifetime value, allowing salespeople to invest in these growth areas and to offer incentives and interactions geared to the customer's individual needs (Loring, 2017). Behavioural analytics and customer profiling may be used to provide salespeople with the ability to personalise interactions to meet the needs of their different customers. Some systems will also have the ability to analyse conversations to identify approaches that increase effectiveness in handling interactions and greater sales successes (Hurley, 2017).

The effects of big data analysis on prospecting for new leads and customer retention: Managing big data is a key area that AI can help to streamline. The prospecting process for new customers is time consuming and frequently leads to disappointment. The AI algorithm can provide an interaction history based on contacts and social media activities (Antonio, 2018) and AI led lead-scoring may be used to identify who is ready to buy, and who in the pipeline is reading to move from prospector to customer. Using AI identified leads enables salespeople to concentrate on a significant number of potentially beneficial sales leads that, once qualified, can be guided through the buying journey towards purchase (Loring, 2017). Therefore, by employing AI systems to identify patterns in customer behaviours it is possible to pinpoint customers in the sales pipeline who are at sales readiness, as well as identifying buying trends in existing markets and the possible emergence of new markets. Unstructured data can be analysed, manipulated and presented in a structured way, so it may be used in the sales process and help simplify sales conversations through the provision of key facts about the customer's interests (www.scientificworldinfo.com). Salespeople may also use AI systems to improve customer retention and optimisation (Loring, 2017). Buyers are kept loyal with customised incentive programs. AI-assisted customer care programs will help to make sure that the salesperson is aligned with their customer's needs and current interests. Realtime purchases in-store and on-line may be increased through point of sales information being provided through conversational interfaces and virtual assistants providing the right information at critical points in the sales process (www.scientificworldinfo.com).

The effect of AI systems on Salespeople's cognitive and professional development: The effects of AI is challenging salespeople to develop new knowledge, skills, including management roles (Loten, 2017). The use of AI algorithms is contributing to productivity and provides sales process enhancement through elimination of non-productive activities and through the removal of mundane jobs. AI can also speed up the sales process by identifying changes in buying patterns and taking over some of the more repetitive administrative roles (Loring, 2018). Salespeople can then concentrate on building relationships with the customers that are identified as having the greatest potential growth and lifetime value by their AI assistant.

Research Questions

- How far should AI be encouraged to take the sales process - human buyer interacting with AI sales assistants, or AI buyers purchasing from AI sales assistants?

- How can big data analysis of social media and other on-line sources be used to allow the salesperson to develop greater adaptability to their customer's needs?
- Will AI free the salesperson to develop higher level, soft evaluative skills and emotional intelligence that are required to handle high level, personalised sales interactions, or consign salespeople to mundane, data driven interactions?
- Will AI standardize sales performance across industries or allow for the development of more individualised sales roles?
- How can privacy and sales intelligence be safe-guarded in an AI driven environment?
- What are the effects of algorithms on customers' behaviour?

3.2.7. Complementary assets and affordable-tech as pathways for AI in the developing world: Case of India - P. Vigneswara Ilavarasan

This section argues that pathways for AI are complementary assets and affordable-tech in a developing country. The development, implementation and adoption of AI are dependent on the first two pathways. The future research agenda should explore possibilities of AI based affordable technologies. This argument is discussed in the context of the developing world countries, using a case study of India.

Studies on the adoption, use and impact of information technology (IT) in businesses or organisations are not new (for instance, Blili & Raymond, 1993; Brown, 2015; Liu, Ke, Wei, & Hua, 2013). The value extraction from IT investments is enabled by the presence of complementary assets (Hughes & Morton, 2006). The complementary assets can be discussed in three major areas ((Laudon & Laudon, 2017): organizational (culture, structure, process and people resources); managerial (top management support, incentives to use, and training); and social (national IT and telecom infrastructure, education, supportive regulatory environment and legislators, and technology business ecosystem).

In a wide range of areas AI can be deployed (please see for a recent review, Duan, Edwards, & Dwivedi, 2019). For instance, Ransbotham, Kiron, Gerbert, & Reeves (2017) highlights that AI reduced the production rate in Air Bus. A quick review (Dutton, 2018) showed that high income countries have either invested money for AI related research or have established institutions to explore the potential benefits. The review also indicates that high income countries are leading the AI bandwagon. Except, India, Kenya and Tunisia, none of the developing world countries are part of this discourse. The presence and absence of complementary assets are likely to influence the trajectories of AI in the developing world. The lessons learnt from India or Kenya experiences are likely to benefit similar low income countries in future. For instance, Pakistan, Vietnam, and others are imitating the success story of Indian software services exports story (Steinmueller, 2001; Yim et al., 2016).

For discussion purposes, we will look at three areas of complementary assets – national IT and telecom infrastructure; nature of enterprises; and regulatory and legislatorial environment. The national IT and telecom infrastructure of the world is captured by the three indices: E-Government Development Index (United Nations, 2018), Information and Communication Technologies (ICT) Development Index (ITU, 2017), and Networked Readiness Index (Baller, Dutta, & Lanvin, 2016). The ranks scored by India are 96, 143 and 134 respectively. These three indices include parameters that reflect the quality of complementary assets. Some of the parameters are Internet users, households and individual subscribers of telephone and broadband (fixed and mobile) per 100 inhabitants, firm level IT adoption, online public services availability and quality of relevant people resources available. As India is doing poorly in the parameters, the overall ranking is low inferring the nature of complementary assets available for the AI domain.

The second area of complementary assets is nature of enterprises in India. An official estimate (Data Gov, 2018) shows that there are 57.6 million enterprises in 2011, in India. Out of the total, 84.5% are own account enterprises. Though the enterprises are employing a larger volume of people, the nature of enterprises indicates poor technological capabilities and small size. An analysis of recent data on

employment published by the government of India (Ilavarasan, 2018) showed that nearly two-thirds of the workforce is employed in small size enterprises. More than half of them are working in businesses with less than six employees. The poor technological capability of these enterprises can be inferred by the fact that two - third of them do not use electricity.

More than two thirds enterprises are owned enterprises. The enterprise owners are likely to less educated. Even AI is made available for the enterprises, the absorptive capacity of these owners, ability to understand the potential that could be garnered while adopting the new technologies (Roberts, Galluch, Dinger, & Grover, 2012), seems to be low. In India, less than one quarter of firms are using AI in their business processes, and start-up ecosystem in the AI domain is miniscule (NITI Aayog, 2018). Not surprisingly, even in the USA, only 17% of the 1500 senior executives surveyed had an understanding of AI and its applications in their businesses (Bradbury, 2018). If AI deployment is possible only in enterprises that are larger with a threshold amount of technological capabilities, the scale of adoption in future will be low in India.

The regulatory and legislative environment in India is positive. The digitisation led policy initiatives collectively called as Digital India pursued by the Government of India are proactive towards AI (NITI Aayog, 2018). The Niti Aayog, the policy recommendation body of Govt. of India is keen on using AI for the national development. The areas designated for change are healthcare, agriculture, education, smart cities and infrastructure and smart mobility and transportation. Out of the listed areas, it is estimated that US\$ 14 billion investment is committed to creating 100 smart cities in India (Pratap, 2015). The government recognises the inadequacies in its machinery. The policy document seeks the private players to participate in the AI development and deployment including the readying the people resources. It is also open to working with others to develop AI based solutions. For instance, Wadhwani AI (<https://eng.wadhwaniai.org/>), a non - profit research institution connects AI experts from universities, grassroots non-governmental organizations and government organisations in developing AI based solutions for social good. At present, the work domains are maternal and child health, tuberculosis and cotton farming in India (Temple, 2019).

However, legislators are likely to prefer AI developments that do not replace people. Frey & Osborne (2017) postulated that AI based automation technologies are likely to displace jobs, even those include cognitive tasks, in the world. Based on their work, there are predictions that 52% (McKinsey Global Institute, 2017) to 77% (Ilavarasan, 2018) of the jobs in India will be automated shortly. Given that the average family, size is four, the impact of automation shall have serious implications. As women and other disadvantaged groups are predominantly doing low skilled jobs, they are also likely to be replaced by AI based technologies (Ilavarasan, 2018). The consequences of the labour displacement might include severe social disorder. No wonder, Mr Gadkari, Union minister has publicly announced that driverless cars shall not be permitted in India¹ signalling no support for AI in similar lines.

In light of the above, we hypothesise that complementary assets are weak or absent for AI in the low income countries. This is the major challenge for the widespread AI adoption and usage in the low income countries. This challenge can be addressed if the AI based solutions are affordable and cater to low technology enterprises or users. There are some positive demonstrations from both small and larger firms. For instance, Get My Parking, a mobile application based solution is being used by low educated parking attendants or contractors in parking spaces in New Delhi.² This application requires low capital and short learning curves. The use of applications like UBER or Google assistant by the drivers in regional languages in their low cost smart phones indicates the adoption of AI based technologies. Get My Parking is a technology start-up whereas Google is a larger technology firm. Small firms are handicapped from lack of access to a larger volume of data which is essential for refining AI solutions, but likely to target markets not catered by the biggies. However, we do not know whether AI ecosystem is dominated by the start-ups or resemble oligopolistic arrangements.

In the light of the above, future research can focus on the following questions:

¹ <https://auto.ndtv.com/news/decided-not-to-allow-driverless-cars-in-india-nitin-gadkari-1964489>

² <https://yourstory.com/2018/01/power-iot-get-parking-wants-disrupt-parking-industry-make-driving-easier>

- What are country specific factors that drive the development and deployment of AI? Also, why India and Kenya are few among the developing countries are exploring the potential of AI than others?
- How do different complementary assets result in divergent AI adoption and deployment levels?
- Do the small firm's dominant industrial structure hinder the AI development and growth?
- Whether the likely users, both from industry and government, possess adequate knowledge about AI and its applications? How does this awareness affect the level of adoption and support for AI eco system?
- Whether affordability is the prime factor for the adoption of AI in the developing countries?
- Whether AI and impact on employment linkages is a repeat of old debate on computerization and labour displacement?
- How do national governments balance the good social potential of AI vis - vis the potential negative consequences for the future of work?
- How can private technology firms collaborate with the national governments in the developing world in developing the required skills and deploying AI based solutions?
- How do start-ups compete with the larger firms in the AI market? Do they focus on different application domains? How do we explain or understand the differences?

3.3. Arts, Humanities & Law Perspective

3.3.1. People-Centred Perspectives on Artificial Intelligence - Jak Spencer

Whilst AI has a multitude of different technological, political and legislative challenges and opportunities, ultimately it has the most impact on people and their everyday lives. People-centred design is a form of innovation that starts with empathy for people and ends with iterative solutions to solve real people's needs. Inclusive Design uses this methodology to create new innovations that meet the needs of the widest number of people as possible, no matter their age, ability, social, cultural or economical background (Clarkson et al., 2003). In recent years, many projects at the Helen Hamlyn Centre for Design, based at the Royal College of Art in London, have focused on the impact and implications of AI in peoples' lives. The challenges, opportunities and future research agenda are outlined below.

Challenges

One of the main challenges regarding the adoption and implementation of AI is the current connotations and perceptions of the subject. To most people, AI is a mysterious concept that is not only hard to define, but also difficult to understand how it manifests itself in their everyday lives. Whilst obviously there are numerous positive uses of AI, many people associate it with negative press and media campaigns depicting AI as the cause of everything from mass unemployed to data breaches, removal of freedom and even full-out global warfare. The ill-defined concept and poor media coverage has given AI a negative brand image, and the jury is still out as to whether the good outweighs the bad.

Once you delve into more detail, further issues arise. The prevalence of biases are now well documented in many of the forms of AI we interact with, from racist financial algorithms to sexist chatbots (O'Neil, 2016). Part of the problem is the controversial role of playing the 'creator'. Artificial Intelligence that mimics human relationships have been created by people with a set of preconceived judgments, moralities, ethics and biases. As O'Neil states "algorithms are just opinions embedded in code" (O'Neil, 2016). Even as we move towards true intelligent robots that can build themselves, they still use human culture as a source for understanding relationships; stereotypes, discrimination, prejudices and all. In one recent example an experimental conversational agent that learnt from Twitter conversations took less than 24 hours before it starting tweeting hateful, racist, sexist and homophobic phrases (Vincent,

2016). One recent study by researchers at the Helen Hamlyn Centre for Design (Spencer et al, 2018) found that the vast majority of digital assistants are portrayed as young, Caucasian, women that enhance the negative perception of the stereotyped role of women in secretarial roles. This is further enhanced by the language used by virtual assistants in general conversation and when responding to certain types of harassment (in one study, none of the major virtual assistants responded in a negative way to being called a slut (Fessler, 2017)).

Of course, many of these issues can be resolved by first questioning why we are looking to develop AI for a particular problem, and what will be the implications for people. At the moment, Artificial Intelligence is predominantly concerned with activities of productivity, efficiency and advancement of business objectives and ultimately increasing growth in the financial sense. In the very near future, we'll be able to have a cup of sugar delivered to our home by drones, work in a completely virtual office with efficient and productive artificial colleagues, or have the latest fashion trend waiting in our size in the wardrobe as soon as we get home. But what if this 'efficient living' isn't entirely a good thing? Many studies have shown that social interaction is fundamental to maintaining good mental health, whilst discovery, taking notice of things around us and serendipity are also important. In Japan, the term hikikomori refers to people who shut themselves off from society, often never leaving the house, relying on one or two close family members, or deliveries from online stores to sustain their lives. In 2016, Japan had 540,000 people aged between 15-39 who had not left their homes in last year (Ma, 2018). People can now live their entire existence without leaving the confines of their own home – and this must be having significant effects on our mental health.

A final note of caution amongst the challenges of new AI is the transition phase between things working with AI capability, and things working with reduced 'smart' capabilities – a phase termed 'augmented intelligence' we are already seeing the consequences of. At best, this transition phase can be confusing and frustrating, at worst discriminating and exclusive. One challenge remains how 'natural' the interaction with AI can be. Whilst in the future, this may be seamless, during this transition phase interactions are still on the terms of what the machine can understand. A recent research participant suffering from early on-set dementia had been bought a smart speaker digital assistant by his daughter to help him with daily activities and reminders. Ultimately it went unused because the participant wanted to 'schedule an appointment in his diary' whilst the digital assistant only understood 'booking an event in the calendar'. In this instance, whilst the technology was advertised as an almost human-like assistant, in reality, users have to learn a new form of interaction, moving from the visual language we use on screens to verbal interactions through speakers and microphones.

Opportunities

Of course, the fact that so many challenges remain can also be interpreted positively with the amount of opportunity there is to improve our interaction and relationship with AI. One obvious opportunity that is already being explored, is the use of AI to enhance 'softer' goals rather than the persistent drive for economic productivity or financial efficiency. Indeed, this is one area where people-centred, qualitative research can really enhance further technological advancements by identifying genuine needs of people to deliver innovations with relevancy that solve real-world problems. With virtual assistants for example, conducting people-centred design research with a small number of diverse people resulted in the creation of an assistant that moved away from the generic stereotypical young, Caucasian, secretarial woman to the development of an older, wiser personality such as David Attenborough or Judy Dench (Spencer et al, 2018). As our interactions with machines start to become more and more human-like, the opportunity lies in the design of these new personalities and the creation of new types of relationship. Should these interactions be on a peer-level, subservient-level or superior-level? Should we treat new technology in the same way we treat our friends, bosses, parents or pets? These are questions that surely have to be answered on a case-by-case basis, and design can help to do this.

Of course, the potential of AI to help solve some of the world's most pressing social challenges is also one that cannot be overlooked. From our ageing population to the loneliness epidemic, from quicker and more accurate healthcare diagnostics to poverty alleviation, AI is helping to shape major global social challenges. Again, to be impactful here is to combine big data with the deep data of design.

Algorithms and intelligence can be designed by engineers and computer scientists, but involving designers who are trained in understanding the needs, frustrations, behaviours and attitudes of real people can provide more innovative and ultimately impactful solutions.

A further opportunity lies in the ‘re-branding’ of AI to something people can appreciate and even rally behind. Often the negative stories relating to unequal, biased or discriminatory algorithms are due to the opaque nature of both the definition and the underlying functionality of AI being misunderstood. Involving designers in the process and involving people helps to create more open, fair and even democratised AI that serves the people.

Research Agenda

One of the most pressing challenges in the development of future AI is ensuring that it is not developed in a silo, without input from other disciplines, and importantly, real people. People-centred design has a history of acting as the ‘cement between the bricks’ of more ‘scientific’ disciplines and can generate impactful innovations in combination with AI. However, more understanding is needed on how the two disciplines can come together and combine in the most fruitful ways. This needs to be not only on a process level - combining two distinctly different disciplines, but also at an organisational and educational level – ensuring that teams dedicated to solving serious challenges have a mixture of disciplines and can develop and disseminate the mixed methodologies they use. The recent acquisition of Datascope by people-centred design firm IDEO, as well as the number of design and data labs being set up by the ‘big 4’ consultancies go some way to realising this, but future dissemination of successful and unsuccessful methodologies is important.

Another important future direction is ensuring that people are at the centre of any AI developments. In the practical sense, this means moving beyond AI for efficiency, towards creating more fair, just and equitable uses that not only improve people’s lives, but also go on to enhance them in the form of creating pleasurable experiences – joy, connection, play and laughter. Transparency can help with this by reducing the mystique and opaqueness of AI to the general public. Acceptance of failure is also important - there will be mistakes along the way, but we need to be accepting of this and learn from them.

And of course, there is still a huge amount of research that needs to be completed on the ethical challenges of introducing new technologies into our lives. What level of responsibility do we give these new machines and what level of blame do they get when something goes wrong? Is it fair to ask machines questions we would struggle to answer as humans? One question that is often asked in the driverless car debate is how an autonomous vehicle would decide who to hit between an 80-year-old or a 3-year-old in the worst-case scenario. But is that something we could answer ourselves? It also opens up other areas of research enquiry, such as brand challenges of AI. A project at the Helen Hamlyn Centre recently reached out to a major global tech company to explore the AI possibility of helping to reduce suicides along a riverfront, but discussions stalled because of the brand implications of being involved in such a sensitive topic and how it might look, despite the success or failure of the technology.

3.3.2. Taste, Fear and Cultural Proximity in the Demand for AI Goods and Services - Annie Tubadji

All industrial revolutions generated not only economic but also important social challenges and opportunities, and yet there is currently no scientific economic recognition of the importance of social changes that may emerge due to the fourth industrial revolution. AI-generated goods and services might be objectively more efficient and less costly than human-made ones, yet we know from the hedonic valuation and behavioural economics literatures that human taste is not based entirely only on the objective characteristics of a product or service. People generally fear what is unknown and new because it brings them feelings of uncertainty. For the same reason they tend to prefer what is culturally closer to themselves. Taste, fear and cultural proximity seem to cause significant biases in consumer behaviour and this will inevitably affect the demand for AI goods and services and yet this issue remains under-researched. Meanwhile, whether AI-induced social changes are palatable to individuals and

society will determine whether there will be demand and therefore whether a market will exist for AI-goods and services.

The first industrial revolution brought the steam engine and it helped travel between continents, trade intensified the growth of cities and slavery was abolished, and laws and institutions evolved. The second industrial revolution brought mass production and the car, which increased urban sprawl, cities grew into megacities, wages increased because factories were more efficient and work times got shorter and all this gradually allowed for the growth of the middle class. The third industrial revolution with the invention of the computer brought increased automation and productivity but also increased pollution as a social aftermath (Langton 1984, Kling 1991). The literature on the fourth industrial revolution however has remained narrowly focused on the question of skills and whether human and AI are substitutes or complements on the labour market (Brynjolfsson and Hitt, 2000; Autor 2013; Katz and Margo 2013; Acemoglu 2014; Frey and Osborne, 2017; Genz et al. 2018). The literature is yet to engage with the significance of social change that will be involved in switching between human-made and AI-made goods and services. AI is intensively used for learning about human demand patterns to serve as a technology that enhances the efficiency of marketing (Kwong 2016) and retailing (Weber and Schütte 2019). Very few studies have paid much attention to the specificities of the demand for AI goods and services, but two examples do exist. The first is a quasi-insight on the demand for goods and services: Morikawa (2017) examines individual predictions about the type of industry that is likely (and thus inferred by the authors to be desirable or more acceptable for the interviewee) to experience substitution of human with AI labour. The other study focuses on the demand for AI services in a very specialized field: Tubadji et al. (2019) look at the demand for robo-advisory services in the banking sector. Apart from these two studies, the topic is largely ignored in the economic literature in favour of supply side research on how producers will be interested in the trade-off between human and AI workers. Yet, the challenges and opportunities of AI-induced social change may have complex implications for the diffusion of AI goods and services and therefore deserve careful examination.

We classify the challenges and opportunities for AI-goods and services in relation to social change and consumer behaviour into three categories: (i) taste, (ii) fear and (iii) cultural proximity. These are overviewed below as follows.

Challenges

Taste is a challenge that hides a double-edged sword. On one side, people adapt relatively slowly and definitely slower than artificial intelligence. The first appearance of the locomotive on film scared people and it took time until cinema established itself as a successful industry. AI might be more efficient and reliable, but using these types of goods and services may face social resistance at least for some considerable time after these services will be possible to offer on the market (Patsiotis et al. 2012). For a market to at all exist, both demand and supply are necessary. On the other side, taste is an unfaithful friend: over-enthusiastic but unjustified embracing of certain products and fashionable tastes creates the famous price bubbles such as the tulip mania. First, just like in the tulip mania bubble, bubbles lead first to massive precarious economic conditions. In the Netherlands, many individuals started to risk their entire economic fortune on obtaining a single tulip bulb. The situation aggravated so much that public policy interventions were due to prevent a national disaster (Garber 2000). Second, taste-driven price bubbles tend to ‘burst’, i.e. price booms are famously followed by deep busts, which are proportional to the size of the boom (Emmett 2000; Breuninger and Berg 2001). Thus, if AI is accepted with enthusiastic fashion, it might explosively spread before the realistic aftermaths from its use get properly perceived and reflected by the demand for AI goods and services.

Fear is known in behavioural economics and prospect theory to be a stronger driver for human choice than pleasure (Kahneman and Tverski, 1979). While AI might be able to decrease our working hours and offer more efficient services, fear about competition for jobs between humans and AI and fear about the unknown impact of AI may lead us to underestimate the gains from AI and overestimate the threats. Thus, we may remove AI from our options for choice much earlier than we should (Shackle 1949). An interviewee’s severity of fear (as opposed to objective knowledge) about AI has not been seriously examined by either Morikawa (2017) or Frey and Osborne (2017). Meanwhile, Tubadji et al. (2019) find that increased experience in using technology is actually associated with an individual’s

disenchantment with the use of robo-advisory services in the banking sector. This finding suggests that even when fear is not initially present, a backlash may originate afterwards from the initial over-optimism about AI goods and services.

Cultural proximity might be the ultimate challenge for the embracing of AI goods and services. The goods and services of the first, second and third industrial revolutions were tools that enhanced what remained a predominantly human production. Steamboats moved people faster across the sea; the automobile made the suburbs closer in time to the city centre for the urban worker; computers connected humans. The negative social effect of Facebook and other known electronic media is based on the fact that they dehumanize social experience and people become less social. People are parochially thinking social animals that tend to exhibit preference for homogeneity, i.e. to show strong preferences for things familiar and similar to one's own identity (McPherson et al. 2001). This latter tendency is often labelled as cultural proximity and is widely researched in the economic literature from Adam Smith to modern regional economic spatial analysis (Torre 2008). Cultural proximity is known to be a key determinant for economic flows for people, goods, financial investments in gravity models – people prefer to live with, trade with and invest in what is closer to their own identity (i.e. the home bias effect) (Tadesse and White 2010). AI lack human identity, so they are by definition at one degree distance from any human. How will this cultural distance between humans and AI interact with people's demand for AI goods and services? Are AI-products real substitutes for human product according to consumers' perceptions? Which products and services will be affected most from the lack of human proximity between the labour employed in these goods and service and the consumer?

Opportunities

Learning about the market **taste** for AI-produced goods and services can firstly improve firms and employers use of AI. While their attention is currently focused on the pros from efficiency gains, they might be overlooking the market reaction to the integration of AI in their production process. Learning about tastes informs the market about AI-generated products and services, which can help determine the quantity of AI-goods and services to invested in. This can prevent producers from being trapped with over-investment in a type of technology whose product might not be readily accepted by consumers. Taste-studies can also signal to the producer if the current high demand is a temporary bubble.

Learning about the **fear** factor in AI-related social opinions and policy-making tendencies can help us make evidence-based AI-related decisions. It will save us from being swayed by bounded rationality in our economic, political and policy-making decisions that relate to this novel technological device.

Learning about the importance of **cultural proximity** in the context of AI-human cultural distance can help to quantify the cultural gravity effect that bounds our consumption of AI-goods and products. Having this quantitative information can serve as a tool for predicting the diffusion of AI-goods and services in a locality.

Research Agenda

Our ability to take opportunities to learn about the effects of taste, fear and cultural proximity on demand for AI-goods and services depends on our ability to adapt the research toolkit and generate the most enlightening answers. The multidisciplinary Culture-Based Development (CBD) 'toolkit' is a combination of moral philosophy, consumer behaviour, behavioural economics and regional economics and should be used because:

- Moral philosophy is optimal for explicating the mechanisms behind moral sentiments and taste (Smith 1759).
- Consumer behaviour is the classical field for studying demand using hedonic modelling of preference and choice (Scitovsky, 1976; Becker 1996).
- Behavioural economics has developed the best knowledge for analyzing fear mechanisms (Kahneman and Tversky, 1979).

- Regional economics is most aware of cultural proximity (Torre, 2008; Tubadji and Nijkamp 2016) and cultural gravity analysis (see Tubadji and Nijkamp 2015). Regional economics has also studied the interaction between cultural relativity and fear and has documented its implications on the percolation of ideas and knowledge (Tubadji et al. 2016).

Thus, a culture-based analysis is required that combines analyses of consumer behaviour and ethical mechanisms using bounded rationality with regard to the consumption of AI goods and services. It would account for the specificity of cultural tastes and fears in each spatially defined market. Analyses are required that identify tastes for the use of AI goods of services, which explore the role of knowledge about and level of fear from AI and investigate regional variations in consumers' AI-related preferences and choices.

3.4. Science and Technology Perspective

3.4.1. Perspectives on Artificial Intelligence in the fundamental sciences³ - Gert Aarts and Biagio Lucini

Research in the fundamental sciences aims to investigate Nature at both the largest and the smallest length scales, at the highest energies, and with complex behaviour emerging from simple underlying laws. In the physical sciences this encapsulates the study of the cosmos, including e.g. dark matter and dark energy, gravitational waves, and black holes, and of elementary particles, including e.g. the Higgs boson, the quark-gluon plasma and new physics beyond the Standard Model. Dynamics at small length scales is determined by the rules of quantum mechanics, rather than classical – Newtonian – mechanics, which introduces an intrinsic indeterminacy in the problem, following the usual probabilistic interpretation. Understanding complex quantum systems, quantum control and quantum information is highly relevant for the paradigm of quantum computing, which surpasses classical computing algorithms in a dramatic fashion and, once available, will make previously incomputable problems solvable. Phase transitions, such as the transition between ice and water, or between magnetic and non-magnetic phases in materials, are manifestations of collective behaviour emerging from simple laws. Order parameters, e.g. the net magnetisation of a material, display the presence or absence of macroscopic order and are connected to the underlying pattern of symmetry breaking, linking phase transitions to the microscopic laws of Nature in a precise way.

The adoption of artificial intelligence (AI) in the fundamental sciences, especially in the form of machine learning (ML), has seen a striking increase in the past 5 years or so (Guest, 2018, Carleo, 2019). While previously a link between ML and the physical sciences existed via statistical mechanics, the methodology developed in physics to analyse large systems with fluctuating degrees of freedom, in recent years the use of ML has exploded and it is now employed in most branches of fundamental science, with increasing success and acceptance.

Challenges

An overview of ML applications across the fundamental sciences (Carleo, 2019) is necessarily incomplete, and most definitely beyond our level of competence. Instead we outline two research areas in which ML and AI are of increasing importance.

The Large Hadron Collider scatters protons and also lead ions at speeds close to the speed of light. Due to both Einstein's theory of relativity and the quantum-mechanical nature of particles at these high energies, many particles are created in these collisions, including rare ones, such as the Higgs boson, which decay almost immediately. Since the number of events at each collision is too large to be stored and investigated afterwards, the selection of "interesting" events, which may contain signals of hitherto undiscovered physics, has to take place in real time, often relying on comparison with simulated data. In the language of ML, this can therefore be seen as a classification problem, with the simulated data

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providing a labelled training set. The challenges here are manifold (Guest, 2018). Searches for new physics may have conflicting demands compared to precision Standard Model measurements, leading to tension in how to handle signal and background. Systematic uncertainties may arise from the use of computer-generated training data and a mismodeling in the simulation. Since the interpretation of the outcome of a neural network analysis is less straightforward than for a more traditional approach, comparisons with theoretical models are more involved. And finally, due to the speed with which AI evolves, it may be difficult to commit to a certain software framework and embed it in existing analysis packages, before the field has moved on.

As a second example, we consider phases of matter easily accessible in the lab, which are highly relevant for technological applications, such as the storage of digital information and quantum computing. A prime case here is given by materials with permanent magnetisation below a transition temperature; magnetic storage underpins the hard disk. Superconductors, which provide another example, can conduct electricity without dissipation – and hence energy loss – at very low temperatures, which can be realised in lab conditions. Superconductivity is a broad phenomenon that includes many different realisations. A currently much studied but not yet understood type of superconducting material is the topological superconductor, which could be used to realise quantum gates for quantum computers or, more immediately, provide superconducting cables at room temperature. In this class of materials, superconductivity is encoded robustly in a geometric property of the material itself in an appropriate abstract representation space. The lack of immediate connection between the latter space and the variables measured in experiments makes it very difficult to identify concrete topological superconductors and characterise them. Here unsupervised machine learning can make an impact, by learning material properties and phases of matter from measured data, without providing labelled training sets. Very recently, first steps in this direction have been made by using ML for phase identification in known systems (Carrasquilla and Melko, 2017), which in some cases provides excellent agreement with theoretical expectations (Giannetti, 2018). Extending this to new, not yet completely understood, systems, could provide an improved way to characterise phases in materials such as topological superconductors (Melko, 2017).

Opportunities

It is easy to identify opportunities where AI and machine learning will benefit the fundamental sciences, analysing the enormous data sets available. Instead, here we will discuss two opportunities where the benefits go both ways, with the knowledge and expertise gathered in the physical sciences yielding a positive impact on AI and ML as well.

In classification problems, ML can be broadly understood as an optimisation problem, in which the parameters of a model function are selected to reproduce as closely as possible the known response on the training set, while avoiding overfitting. In practical applications, this problem requires the use of computational resources. With the growth of the data available and the necessity to obtain a model in the shortest possible timeframe (especially in applications in which inferences are time-critical, e.g. in the financial market or in weather forecasting), the availability of algorithms that are as fast as possible becomes paramount. Computationally power-hungry problems of this type have been well known in Science and Engineering, where they have been addressed with excellent outcomes using a set of techniques collectively known as parallel programming, which allow to distribute the calculation on fast interconnected nodes of a computational ecosystem referred to as a Supercomputer. This by-now mature approach to number crunching, known as high-performance computing (HPC), is offering the possibility to accelerate ML algorithms by orders of magnitude, making tractable problems that previously were not, or shortening the time to solution to a point when a prediction can find timely applicability. Not only is HPC tremendously improving the opportunities provided by ML (Berhofer, 2018), but the synergy goes also in the opposite direction, with disciplines traditionally harnessing HPC benefitting from novel ML approaches. An example is given by calculations in which a set of parameters would need to be optimised. In traditional HPC applications, this problem has been approached with expensive grid searches, sometimes informed by educated guesses. ML offers a radically new approach, which, in addition to the optimisation of existing algorithms (Shanahan, 2018), can potentially lead us towards the discovery of new and more efficient ones (Liu, 2017). Indeed, the convergence of ML and

HPC, sometimes referred to as high-performance data analytics (HPDA), is one of the most promising and potentially disruptive trends in AI, which both fields can benefit from enormously.

A second opportunity is given by the training and development of the next generation of data scientists. The demand for highly-skilled data scientists has been well publicised and is largely driven by the increasing use of AI and ML across many applications in business, industry and healthcare. Fundamental science plays a dual role in this: while AI and ML are used to interrogate scientific data and enable scientific discoveries, in doing so the involved scientists develop valuable data skills easily transferrable to other disciplines, in- or outside science. This is especially so for the next generation of postgraduate students and early-career researchers, for whom training in AI and ML will be intermixed in the research and skill development from day one. In this context, it is interesting to analyse the outcome of the recent funding call of UKRI – UK Research & Innovation, bringing together the seven UK Research Councils, Innovate UK and Research England – for investment in 10-20 Centres for Doctoral Training (CDTs) focussed on areas relevant to Artificial Intelligence (UKRI, 2018). This call, run across the entire UK research landscape, invited proposals for CDTs to “train the research leaders of the future and equip them with the knowledge, skills and creative approaches the UK requires.” Out of the 84 submitted outline proposals, 37 applicants were invited to develop a full proposal (UKRI, 2018). 16 of these were funded (UKRI, 2019). The main focus areas of these 16 CDTs are listed in the table below. Note that each CDT will train, from October 2019 onwards, at least 50 postgraduate students, in 5 cohorts of 10, via a 4-year cohort-based PhD programme.

Table 2: Focus areas of the 16 funded Centres for Doctoral Training in the 2018 UKRI AI CDT funding call

Focus area	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Healthcare, biomedical	✓	✓	✓	✓	✓											
Responsible AI, human						✓	✓	✓	✓							
Core AI research					✓					✓						
Fundamental science					✓											
Language processing											✓	✓				
Environment, sustainability													✓	✓		
Engineering, nano-devices															✓	
Creative industries, music																✓

Perhaps not unsurprisingly, the majority of the funded CDTs will be active in the areas of healthcare and biomedical research, and of responsible AI, with a focus on accountability, transparency, and the societal and human perspective. Two CDTs are active in the areas of core AI research, language processing, or sustainability and the environment, and one CDT in the development of nano-devices or the creative industries. Only one CDT has a partial focus on fundamental science.⁴ It seems therefore that the training opportunities offered by the use of AI and ML in the fundamental sciences are not yet developed enough to convince the main funder in the UK, providing therefore a clear opportunity for the future.

Research Agenda

Fundamental science offers a distinctive but generalisable perspective on future research in AI, as most of the challenges it faces are complex and at the same time deeply rooted in an approach that has evolved from a long tradition in which practical realisations of experiments, theoretical models, and the underlying philosophy are intertwined and entangled in a coherent structure.

For centuries, the route to scientific discovery has followed the scientific method, i.e. observations lead to the formulation of a hypothesis; data is collected to refute or confirm this; subsequent refinements lead to further understanding, culminating in a theory capable of not only explaining all observations so far, but also able to yield new predictions. One may say that artificial intelligence and machine learning represent a new paradigm to do science, inverting the scientific method, by putting data first, especially in the context of unsupervised learning. By inferring patterns from large sets of data in an

⁴ Disclaimer: the authors are PI and technical director of CDT #5, see cdt-aimlac.org.

unbiased manner and building theories to explain these patterns, one skips over the step of testing hypotheses and hence removes bias in the data analysis.

Indeed, most of the current physics experiments are designed with a bias. For instance, the searches for new particles at the Large Hadron Collider are based on models developed over many years. These models require specific signatures to pick out interesting events. Hence, in a specific search, a trigger will discard all events not containing those signatures. It is natural to ask whether in this way too much information is thrown away, perhaps related to novel interactions and particles that are not part of any currently known model and hence cannot be selected. The question is whether an appropriately setup multi-agent system would be able to select events without a bias, hence leading us towards the discovery of new laws of nature. A similar logic could be applied to most disciplines. Automated science discovery is henceforth a very relevant subject, which should be high in the research agenda.

Automated science discovery cannot be disjoint from interpretability. Outside fundamental science, practitioners of AI and ML are often interested in answers, without associating them necessarily to a complete understanding of how they are obtained, provided that the outcome is reasonable and looks robust. In fundamental science, one would need to go one step further, since from those answers physical laws need to be inferred. This would involve “opening the black-box” (unboxing) that has determined the observed outcome, a long-standing problem in AI, to deduce physical properties from the mathematical expressions the system has worked out for classification or clustering. An example of a successful inference along this line has been provided recently (Wang, 2016). The insights and techniques developed in this area of research would have a wide impact, as unboxing is important for the acceptance of AI approaches in general, with important applications in e.g. the medical and healthcare sector. Finally, a natural follow-up question is whether the inference of the laws governing a phenomenon can be delegated to a second machine, hence going full-circle in the AI-based approach to the fundamental laws of nature.

3.4.2. Science and Technology Studies - Vassilis Galanos

The present contribution to the joint opinion article comes from my recent investigations and preliminary findings from a Science and Technology Studies (STS) perspective on the social dimensions of AI, robotics, machine learning, and other related meshed and hardly defined concepts. One of my findings is that the clear cut division between challenges, opportunities, and research agenda is quite difficult to achieve. Arguments of challenges reveal opportunities and acknowledgment of opportunities are alternative statements of research agenda points.

The recently appointed House of the Lords’ Select Committee on Artificial Intelligence (HLSCAI 2018) identifies AI as part of UK’s industrial sector and recommends that: “the Government must understand the need to build public trust and confidence in how to use artificial intelligence, as well as explain the risks” (25). Most challenges identified there are industry-oriented (for example the knowledge transfer from the Academy to industry as well as the data divide between such spinouts, start-ups, small and medium-sized enterprises and large corporations), educational challenges (introducing AI awareness courses at schools), reality distorting challenges due to AI algorithms (eg. fake news), liability issues between individuals or companies when AI decisions lead to harm. In the same report’s final Appendix, the authors point out that “[c]urrently, EU regulations limited what could be done in this area, but post-Brexit, some attendees felt that there would be opportunities to reassess this” (178).

Previous AI policy documents from the EU, UK, and US (all published in 2016 and of which a good summary and a philosophical review can be found in Cath et al. 2018) have been found to be quite unrealistic in their proposals. The more recent Rathenau Instituut’s report (Van Est, Gerrutsen, & Kool 2017) on Human Rights in the Robot Age: Challenges Arising from the Use of Robotics, Artificial Intelligence, and Virtual and Augmented Reality written for the Parliamentary Assembly of the Council of Europe (PACE) is rather well-informed and examines the relationship between “self-driving cars, care robots, e-coaches, AI that is used for social sorting, judicial applications of AI, and virtual and augmented reality” and “the right to respect for privacy, human dignity, ownership, safety, responsibility and liability, freedom of expression, prohibition of discrimination, access to justice and the right to a fair trial” while they also recommend the discussion of “two potential novel human rights”

in light of AI/robotics-related advancements namely the “right to not be measured, analysed or coached.” These two policy documents are, in my opinion, the ones closest to technical and social reality, although, a careful reading pinpoints to the very fact that the great lack of empirical data makes all speculation a challenge in its own right. This is the reason that the most fundamental challenge (and opportunity) to remember is that despite the fact that AI has been very hyped in the last five years, a disciplined turn to specialists and the grounding of research agenda on the basis of technical evidence should be a core priority of any work dealing with the politics and economics of AI.

Challenges

What are usually presented as AI-related challenges appear to be diversions from rather real-life problems and have little to do with current capabilities of AI. This happens because the very term AI is at the same time ill-defined but also loaded with meaning, expressing hopes and fears ranging from the will to understand intelligence to the consumption by one’s progeny (in this case, intelligent robotic overlords) (Szollosy 2016). AI is specific enough to cause sensationalist alarm and/or excitement, and vague enough for many commentators to interpret it according to their own agenda(s).

This brings us to the very first actual challenge of AI, which has to do with the **problematic aspects of the term**. As argued (Galanos 2018b), both terms “artificial” and “intelligence,” if examined separately have been contested for their rigidity and usefulness. The differentiation between natural and artificial (or nature/nurture, nature/culture, and other similar divides) is impossible to define as either all reality is natural (an outcome of the same nature; naturalist perspective) or all is constructed (interpreted within human brains, a loose constructivist perspective). Such distinctions are posed usually with the conscious or unconscious intention to either “naturalise” (hence justify) certain behaviours (“this is unnatural!”) or to imply human supremacy over nature. Both cases are associated with scenarios of more-than-human or less-than-human, found in horror stories as well as science fiction.

All in all: the “artificial” in AI is in itself a terminological challenge. Similarly, several cognitive scientists, cyberneticians, system theorists, AI/robotics specialists, and sociologists argue that AI is merely indefinable because we do not have any good understanding of the word intelligence. (ibid). From empirical data I am gathering at the moment, interviewing specialists with direct (or somewhat direct, given the ambiguity of the term) involvement in AI R&D, I begin to shape the view that specialists are particularly sceptical when it comes to use the term – most of them tend to “unmask” the term and provide with names of other technologies expressing a syllogism of the type “when people speak about AI, they basically mean x(machine learning, the internet, algorithmic training, deep learning, data science, and so on)” – for the “elderly” AI generation, AI has nothing to do with what is now portrayed as AI, as “true” good ol’ fashioned AI (GOF AI) is based on different techniques and methodologies; also has different purposes (for these and other debates on weak/strong AI see Brooks 2002; Pickering 2010; Searle 1980). This poses very practical challenges in cases such as when convoluted networks are used to generate deep fake videos; these may be perceived on behalf of the public in tandem with a generalised distrust and less confidence towards (digital) media and the fact that convoluted networks are very easily masked as “AI” allows the AI-as-an-enemy narrative to continue in a meshed context of various overlapping technologies. Similarly, robotic hoovers sending data to third parties, generating mirroring effects of targeted advertising, show the data-intense problematic which lies behind (and basically allows the existence of) AI fearful hypes.

A more tangible challenge is the data basis of what constitutes contemporary commonly perceived AI – and in particular the **data wealth problematic**. In a nutshell: my “AI” will differ to yours if we don’t have the same data sources or if you are a company and I am an end-user. (Although this appears as a data ethics/politics argument, given that data is the bread and butter of current AI, I believe it is worth to mention). Sawyer (2008) identifies a gap between data rich and data poor in contemporary cyberinfrastructure. Given that the main reason behind current success in the development of AI is essentially the massive generation of data allowing the 1980s pattern recognition-based machine learning algorithms to produce fruitful patterns a data wealth analysis should become part of top-priority setting when it comes to the economic development of various layers of the market (eg. data/AI emperors versus start-up AI-based companies) but also with regard to one’s personal control of data and the awareness of the various type of uses of their data. A number of recent works have shown (a)

the interconnectedness and historical association between automation, data-driven, and AI technologies, and (b) how one of the main problems arising has to do with the generation of new inequalities and the perpetuation of older biases relating to all intersectionalist concerns with race, gender, sexual orientation, species, age, and other problematic human categories (eg. Eubanks 2018; Buolamwini & Gebru 2018; Prainsack 2019). To tie this with above statements, the AI hype and ill-definition diverts focus from problems which should be prioritised instead of policy discussions having to do with robotic liability, and so on which take non-experts' accounts as expert knowledge and science fiction plot devices such as Asimov's laws of robotics at face value (eg. European Parliament 2017).

My conviction for this conceptual and terminological burden (which, more than specialists who do not pay attention to definitions as long as things work, does impose problems to other users of the term) is that researchers examining the sensitising concept "AI" should borrow descriptive terminology from similar cases of other studies in complexly defined technologies. One is the understanding of AI as rorschach, that is, as a psychologist's inkblot shown to the patient, upon which patients project their hopes and fears (borrowed by Turkle's 1982 "Computers as Rorschach" metaphor). The second, more concrete, and with applications in policy, industry, and other relevant social clusters, is the understanding of AI as institutional hybrid, that is, a term quite problematic which needs to be reinterpreted according to the needs of different actors (a lawyer understands AI in a way different to a policymaker, in a way different to a journalist, in way different to a bioinformatics specialist, in a way different to a sci-fi fan, and so on).

The agenda purpose then would be to create typologies of different understandings of AI according to different players/institutions/arenas/other social clusters (this approach borrows largely from Haddow et al's 2010 work on xenotransplantation as well as Brown and Michael's 2004 work on biotechnology and how different types of transplants and "risky creatures" were found extremely difficult to fit in various seemingly unconnected areas). A final framework to keep in mind when examining AI terminology (and rhetoric) is Donald MacKenzie's 1999 certainty trough based on an x-y ratio where x represents the proximity to the production of technology and y the degree of certainty. Drawing from missile technologies, MacKenzie proposed that more and the less directly involved one is with the production of technologies, the more uncertain they are – the public knows nothing about it, hence they are uncertain; the developers know way too much, hence they know what might go wrong, so they are uncertain; the in-between intermediaries (promoters, commentators, managers, spokespersons, etc) with little involvement in the production wish to appear convincing to the public (buyers), hence their certainty appears to be high (thus, the trough, MacKenzie 1999). In the case of AI, as I have examined it, this has little to do with promoters as much as it has to do with philosophical, futuristic, and journalistic narratives, perpetuating alarming concerns based on very poor evidence (I do have counter-evidence, for example, on Nick Bostrom's 2014 very poor empirical data justifying his superintelligence theory, however, it would go far beyond the scope of this paper to explicate).

This challenge, that is, **the intrusion of non-experts to AI debates** (or, to be more precise, the development of AI debates by non-experts), I have examined in a recent paper (Galanos 2018a). I believe that the 4-year period 2014-2018, if examined carefully from a media+policy perspective shows the crystallisation of a third AI hype (after the pre-Lighthill and Alvey Programme ones described in Dwivedi et al. 2015), established through public commentary by prestigious public personas such as Stephen Hawking, Elon Musk, and Bill Gates who, after using their credentials in domains other than AI, promoted AI doomsday scenarios which found their ways into policy discussions. One of my current hypotheses (to a certain extent verified from various recent initiatives which have not yet taken the form of papers but can be traced in the news or in academic contexts) is that the hype is now entering the trough of Gartner's disillusionment (Linden & Fenn 2003) and the most important thing to avoid is an upcoming third AI winter. Concerns about a third AI winter have been expressed by AI specialists such as Booch (2015), and now that a general realisation of the fragility of ultraintelligence/singularity/superintelligence types of arguments (for a concise review of the arguments see Eden et al 2012; for their most recent instalment, Bostrom 2014) has become relatively fashionable (as I often say in my talks "unhype is the new hype"), it is time to strategically intervene and promote justifiable (and yet opportunistic) agendas in AI.

Opportunities

I find out that clear separation between opportunities and research agenda is relatively difficult to achieve, especially if one follows a relatively sceptical stance towards AI. Hence, I will keep the section on opportunities short and focus more on the agenda below; moreover, opportunities impose expectations and, especially in the case of AI, far-fetched expectations have been harmful. This brings me, however, to the first opportunity (resulting from an earlier challenge).

History of AI shows a repetitive rise and fall pattern of hype and disillusionment; large availability of grants followed by long periods of research support stagnation – this happened because AI specialists, in their attempts at establishing their field have made very brave and overly ambitious (and ambiguous) promises to eventually remain unfulfilled (Fleck 1982, Crevier 1993). It seems that the promissory arena has changed and, as it has been shown, in a dangerous fashion for policy (Galanos 2019), a large amount of negative promissory work has now shaped public opinion through the input of science-related prestigious personas (eg. Stephen Hawking, Elon Musk) whose undeniable expertise in certain fields allows them to acquire imaginary credentials to become spokespersons of any other “hot” technical/scientific subject. The availability of previous historical sources on the first two rounds of negative effects of promissory work gives the opportunity for a strong basis for (a) investigating in detail the relatively undocumented history of AI past the early/mid-1990s and (b) given the evidence of the current negative effects of non-specialist intrusion, the right to intense boundary work to separate who is entitled to be a spokesperson of AI and who is not.

Research councils, whose active interest in AI is relatively recent (eg. in the UK, the Eight Great Technologies report was published in 2013) and hence their needs appear modifiable, should be approached by academics investigating AI in an empirical manner and be recommended that certain AI-related challenge funds should be dedicated to (a) explainability/intelligibility of AI/machine learning “black-boxes,” (b) to work evidencing that AI (like every technology) is about augmentation of human skills and not abrupt replacement which is found to be nearly impossible in most cases, and (c) to promote in every institution, spinout, and laboratory a framework of strategic foresight (constructing plans and setting goals for a maximum of 3-5 years) instead of circulating abstract expectations looking forward to several decades (cf. the proposals by Van Lente (2012).

Research Agenda for Policy and Research

- Investigation of the relationship between available data and unrepresented groups – a good case can be made in medical applications of machine learning when it comes to rare diseases. The development of a strong novel economic framework which will deal with the question of assigning value to data. Whereas traditionally the accumulation of some source tends to decrease its value, with data the opposite seems to appear: the more, the better. What are the implications of such a reversal? Is it really a reversal?
- Further, with machine learning as a point of argumentation departure, a consideration of a possible alteration of data protection legislations (eg. GDPR) which will enable people with minimal access to data to be represented.
- Push forward an agenda which will strongly suggest the involvement of social science scholars with expertise in AI-related topics as members of science and technology research committees (eg. House of Lords, EPSRC).
- As a subsidiary to the above, such social scientists should be responsible for the boundary work between who is entitled to become a witness for such committees and to ensure that the conductors of reports “ask the right questions” instead of biased, (mis)leading, and irrelevant ones.
- Emphatic recommendations for balancing the overwhelming amount of speculative, future-oriented studies on AI (which usually take a technologically deterministic view of the “how AI will change society” type) with empirical-driven research in terms of the history and sociology of AI, separation of actual versus imagined capabilities and challenges.

- Several “elderly” or “traditionalist” AI scholars may agree that the quest of create AI in the early era of the field was mainly the quest to understand intelligence at large (or at least human). Contemporary rhetoric on AI seems to take for granted that humans know what is intelligence and that there should be concerns of the hubris relating to the creation of artificial intelligence. AI (and especially robotics) specialists have to a great extent turned to bio-inspired and nonhuman-centric approaches to achieve small successes, little by little (eg. Brooks 2002) suggesting that we cannot make purist AI since we do not know what is intelligence. A generalised support of the return to the notion that AI should enable the understanding of intelligence should be fruitful for research as it will allow an escape from current misinformed narratives concerned with hubris.
- Based on the recommendations by Winnograd & Flores (1986) and their more recent revisit by Collins (2018), and if the achievement of a more “original” GOF AI (good ol’ fashioned AI) is desired, special grants should be given to natural language processing instead of machine learning. The latter has developed up to a significant degree to assist new findings related to NLP (for example, the intricacies of language as a form of commitment to social obligations and as a social act – or “speech act”) with the assistance of current machine learning algorithms which will enable the understanding of previously unsolvable correlations.
- A constantly reassessed mapping of actors and players shaping the sensitising concept “AI” should be generated in order to gain clearer views of the currently developing system which underpins the AI confusion – how do the not-so-separate-although-sufficiently-distinct clusters of AI developers, AI industrialists, AI commentators and futurists, journalists, end-users of every sort (from Amazon customers to doctors making use of new AI tools), policymakers, science fiction authors and film industries (and so on) relate to each other? How do their relationships change and how does this effect the overall shape of the technology and the public portrayal of AI? An interactive map of such relevant social groups or niches should become available to all such members to raise awareness of the generalised messiness of the meaning of AI.
- The organising of an activist niche which will take mostly into account people with academic expertise in technical/practical AI-related fields which will bring forward and publicise an agenda to discuss the dangers and possible advantages of autonomous weapons; in other words, the opposition between the questions “why make weapons in the first place?” and “if we are to have weapons, why not make them as accurate as possible?”

3.5. *Government and Public Sector Perspective*

3.5.1. Artificial Intelligence in the public sector - Rony Medaglia

A key area of application of AI technologies is the one of the public sector. The core difference between AI technologies and traditional office automation is that the former do not only support decisions on a pre-programmed if-then logic but, instead, feature learning capabilities (Russell & Norvig, 2016). Given this characteristic, AI presents a special range of opportunities and challenges in a public decision-making context, where environmental variables are constantly changing, and pre-programming cannot account for all possible cases.

AI technologies, such as machine learning, rule-based systems, natural language processing, and speech recognition, when adopted in the public sector, carry potential implications for all aspects of government actions, including the inner workings of government agencies, the relationship between governments and citizens, and the role of governments as regulators (Eggers, Schatsky, & Viechnicki, 2017).

Here we outline the key challenges and opportunities of the specific application of AI in a public sector context, and present a research agenda.

Challenges

A number of challenges related to AI adoption in the public sector are not unique to AI, but instead overlap with well-documented problems of adoption of any new emergent technology in government. These classic challenges include: the quest for data integration across different organizations, resistance to use by the public sector workforce and citizens alike, and threats of labour substitution (Sun & Medaglia, 2019).

Conversely, we also would like to pinpoint three specific challenges in the adoption in the public sector that are unique, or especially relevant, to AI: algorithmic bias, algorithm opacity, and filter bubbles.

The first challenge concerns algorithmic bias. AI-based algorithms are increasingly being experimented by governments to introduce efficiencies in the large scale customization of public services, a type of task that draws on citizen profiling (Janssen & Kuk, 2016b). Examples of such applications include public hospitals using machine learning algorithms to predict virus outbreaks (Mitchell, Meredith, Richardson, Greengross, & Smith, 2016); analytics tool used to predict hotspots of crime (Goldsmith & Crawford, 2014) and high risk youth (Chandler, Levitt, & List, 2011); and AI systems used to target health inspections in restaurant businesses (Kang, Kuznetsova, Luca, & Choi, 2013).

While the ability of AI applications to recognize patterns can be beneficial to segment populations for e.g., welfare service provision or addressing anti-social behaviour, it can also amplify discriminatory biases that are already present in human-led assessments: predictive algorithms, in fact, can favour groups that are better represented in the training data (Barocas & Selbst, 2016). Algorithms can thus lead to systematic and unfair treatment of citizens based on social biases of gender, race, sexuality, and ethnicity – an outcome which is in direct conflict with the mission of governments of unbiased treatment of citizens under the rule of law.

The second challenge concerns algorithm opacity. The increasing complexity of AI systems, such as machine learning and neural networks, reduces the capability of human operators to trace outputs back to specific inputs, making it potentially impossible to clearly account for specific AI-driven outcomes. The wider consequences of this phenomenon have been referred to as creating a “black box society” (Pasquale, 2015), and have profound implications for governments which, by definition, are bound to citizen expectations of transparency and accountability. A clear example can be found by looking at how digital systems impact the work of street level bureaucracies. While, on the one hand, automated decision-making has the potential to improve fairness by reducing the discretion of public service operators (Busch & Henriksen, 2018), on the other hand AI systems can remove public servants from the duty of accountability, exacerbating the phenomenon where citizens are faced with impotence in front of “the computer says no” responses (Wihlborg, Larsson, & Hedström, 2016). The opacity of mechanisms in AI-supported decisions poses challenges not only in the ethical responsibility and legal liability dimensions – who is responsible for a damage to a citizen stakeholder, if the decision has been outsourced to an AI application? – but also to the wider fundamental issue of political accountability of public governance.

The third challenge is associated with the creation AI-enabled filter bubbles in the public sphere. AI-enabled algorithms have proven tremendously effective at micro-targeting content and at fostering a booming constellation of groups of like-minded actors in the public space, such as social media platforms (Sunstein, 2017). This challenge affects the context in which public governance is exercised – that is the sphere of public opinion formation at large and thus, indirectly, the ability of government to both be seen as legitimate by citizens, and to formulate policy actions that draw on a perceived common good. The ability of algorithms to provide personalized content by filtering out inputs that do not match pre-existing user preferences (in e.g., news, entertainment, political discourse) is potentially bringing about societal fragmentation, polarization, and radicalization, with the creation of digital echo chambers (Medaglia & Zhu, 2017). Governments that fail to mitigate such disaggregating forces, enabled by AI systems, will potentially lose the capability to be perceived as legitimate and to formulate policy actions that can be met by sufficient public opinion support.

Opportunities

The introduction of AI in the action of government comes with a wide range of unique opportunities. While many of them start to be highlighted in a booming number of viewpoints on AI in the public

sector (Desouza, 2018; Duan, Edwards, & Dwivedi, 2019), we focus here on two specific ones that we consider outstanding: relieving cognitive resources of public workers, and fostering citizen trust.

First, AI applications, such as rules-based systems, speech recognition, machine translation, computer vision, machine learning, robotics, and natural language processing, have the potential to free up precious cognitive resources of public workers, which can then be allocated to tasks of higher added value (Eggers, Schatsky, & Viechnicki, 2017). This reallocation allows government to focus scarce resources on tasks at which human workers perform better than machines, such as problems solving activities that require empathy, creativity, and innovation.

Second, AI applications have the potential of fostering citizen trust. The other side of introducing “digital discretion” in the work of street level bureaucrats by AI systems is that unfair, inefficient, or distorted provision of government services can be potentially reduced, thus increasing citizen trust towards government. The introduction of traditional digital government initiatives has already been documented as helping reduce public servant corruption (Bertot, Jaeger, & Grimes, 2010): AI systems can bring this trend further, provided that governments put great care in ensuring that the adoption of AI is included in a context of dialogue with citizens, and towards counteracting the increasing distrust towards governments. Both the ability of AI systems to micro-target policy recipients (which allows governments to implement much more fine-grained policies), and to ensure real-time, flexible rule-based action by street level bureaucrats (which reduces arbitrariness and citizen divides in service provision), can potentially enhance citizen trust towards governments.

Research Agenda

The layered nature of the potential disruptions in the introduction of AI in the public sector calls for a renewed research agenda, and new theorization efforts (von Krogh, 2018). Here we identify three key areas of research, to be prioritized in the near future.

First, there is a need to unpack the impacts on the public sector workforce of delegating decision-making to AI. Besides highlighting the classic threat of labour substitution, what the introduction of AI systems calls for is research on the nature and the mechanisms of transformation in the public workforce. Automated systems can undermine worker motivation, cause alienation, and reduce satisfaction, productivity, and innovation (Moniz, 2013). Research questions worth investigating will thus be: what are the motivational and psychological impacts of introducing AI as a “digital colleague” on the public workforce? How are inter- and intra-organizational dynamics of power in public agencies shaped by the introduction of AI?

Second, there is a need to better understand the dynamics in the attribution of meaning to AI-supported public decision-making. As AI applications tend to introduce opacity, and reduce the ability of non-experts to audit the mechanisms that lead to decision outputs, we need to unpack the novel sensemaking processes enacted by government workers and citizens alike, when facing AI applications. Examples of research questions include: how do policy makers frame and legitimize AI-supported solutions? How do citizens perceive the role of AI in policy making? How is agency attribution formulated and negotiated between different stakeholders in the government sphere?

Third, there is a design research challenge to tackle the issue of the potential opacity of AI applications. The nature of AI algorithms seems to suggest that their transparency, traceability, and explainability are inversely proportional to their complexity. While this might be the case, there is no reason to consider such characteristics as immune from mitigation strategies in the design and management of AI applications. Research question related to this challenge include: how to design algorithms that enable explanation? How to design evaluation frameworks that avoid discrimination?

The introduction of AI in the public sector opens up new scenarios for practitioners and researchers alike. Being able to understand and act on these scenarios becomes now of utmost importance.

3.5.2. AI for SMEs and Public Sector Organizations - Sujeet Sharma and JB Singh

Artificial intelligence (AI) technologies though gradually developed in the past several decades, has shown more potential for business enterprises in the past couple of years due to promising development in machine learning algorithms, rise of big data, and low cost processing power due to the advent of cloud computing. Though, AI is the constellations of a set of technologies such as machine learning, deep neural networks, natural language processing, robotics etc., however in simpler terms it can be defined an advanced prediction technology (Agrawal et al., 2017). In this sense, AI technologies find pattern in large amount of data and provide predictive outcome for the new similar instances. The well documented AI applications such as cancer detection in health care and fraud detection in financial industries are promising. AI applications in various industries and activities such as manufacturing, human resources, and sales and promotion are growing, however such applications are currently limited to mainly larger business enterprises.

Opportunities

Artificial Intelligence applications have potential for SMEs, public/government organizations and also not-for-profit enterprises where the potential has not yet significantly explored. The potential of AI in SMEs are particularly in automation of various tasks with decision making components such as in the functions of finance and customer services. For example, AI applications could help SMEs in matching customer invoices with received payments, AI chatbots could help these enterprises answering customer's simple requests. These are some easy to implement applications where AI could improve the efficiency of SMEs. Unlike SMEs, public sector and government organizations generate lot of data through their processes and hence more potential for application of AI technologies. In developing countries particularly, payments of the welfare schemes to the eligible citizens is paramount in functioning of the state. One of the problem in developing countries is the leakage due to corruption and appropriation of such schemes by the elites or the well-connected set of people. AI could help in identifying the target citizens for such welfare schemes and payments. Another promising area of AI applications could be in judiciary in developing countries where cases are pending from decades due to availability of limited resources. AI could help in deciding on the bail hearings in courts as machine learning technologies are now robust for such applications (Mullainathan & Spiess, 2017) and may deliver decision which might not only be quick but also more accurate.

Similarly, AI opportunities also exist in the not-for-profit enterprises, one of the fine examples is Akshaya Patra in India⁵, which runs world's largest mid-day meal program serving wholesome food to the children of government and government aided schools which has the aim of reducing malnutrition and facilitating the right to education of socio-economically disadvantaged children. Here, AI could be used to accurately forecast the demand of the meals for schools based on the data of student's attendance records and hence greatly minimizing the waste of food (Raval, 2018).

New technology adoption in SMEs and public sector enterprises generally followed by the adoption in large enterprises when such technology becomes stable and affordable. However, in case of AI applications cost may not be the bigger issue as the supporting software programs are increasingly also available as open source⁶. SMEs and public sector organizations need to understand the capabilities of AI technologies and should work towards appropriating these capabilities for solving existing business concerns. In the current scenario, most of the popular AI applications in media reporting are of large and information technology intensive organizations.

Challenges

The large private sector companies like Google, Facebook etc. are adopting artificial intelligence enabled tools to obtain competitive and strategic advantage in the digital marketplace. These companies maintain enough information resources in terms of information technology assets and capabilities to exploit data for better decision-making. However, SMEs and public sector companies may face some

⁵ <https://www.akshayapatra.org/about-us>

⁶ <https://dzone.com/articles/how-open-source-software-drives-iot-and-ai>

challenges in leveraging artificial intelligence enabled tools. There are many challenges in adopting AI based tools ranging from data quality, privacy/security risks and to the shortage of qualified AI experts. In this section, we attempt to describe some of the major challenges faced by SMEs and public sector companies.

Data quality: Data quality can be thought of as the fitness of data to obtain actionable insights using appropriate analytical tools (Lee, 2017). Data noise, data heterogeneity, imbalanced data, data discretization are some of the prominent reasons of low quality data. In the popular epic poem Rime of the Ancient Mariner, author stated that, “Water, water, everywhere, nor any a drop to drink.” The usefulness of the data depends on the quality of the available data in the companies’ warehouses (Hazen et al., 2014). Low quality data lead to the poor decision-making and as a result loss in businesses. The cost of the low quality data may lead to loss of 8% to 12% of the revenue in an organization and may translate in the loss of billions of dollars in a year (Dey & Kumar, 2010). As most of the data collected over a couple of years is unstructured and amassed from multiple sources, the overall quality of collected such data is assumed to be low in the SMEs and public sector companies. If low quality data is used to train AI enabled tools, it will lead to disaster. In public sector organizations, there are rarely available data standards to collect and store data which results in low quality. Therefore, data quality is one of the key challenges in the adoption of AI enabled machines and becomes severe in SMES and public sector enterprises.

Privacy/security risk: Privacy and security are key challenges in adopting AI enabled tools in any organizational settings. These challenges become severe in case of SMEs and public sector organizations due to availability of limited resources. In general, SMEs works under severe constraints of ICT resources and their primary objective is to buy and sell products. In this process, SMEs generate reasonably good amount of data related to product and users. There is a challenge to maintain privacy and security of such useful data. In public sector enterprises, there is a huge amount of personal data being generated during citizen centric services rendered by government agencies. This huge amount of data is vulnerable to data theft or data manipulation as ICT regulations are quite weak in many developing countries. In addition, privacy is a major contributor of legal and ethical concerns raised by the rapid growth of AI enabled products in past couple of years. Duan et al. (2019) discussed that ethical and legal issues are major challenges of AI enabled services.

Shortage of qualified AI experts: In SMEs and public sector companies, decision makers are attempting to employ AI to see positive impacts on the business outcomes and hunting for AI experts to transform their vision into reality. Bernard Marr (2018) reported that there is a requirement of one million AI experts worldwide but available AI experts are about 300,000. Bernard Marr (2018) further argued that the shortage of AI experts is due to the mismatch between skills taught in an academic environment and skills expected to keep pace with new AI technologies. In addition, there is a well-established relationship between artificial intelligence and data science. In fact, AI is considered as a tool to data science that provides actionable insights to a particular problem. In a recent study, The Economist Intelligence unit (2018) conducted a survey of 400 senior executive working on the transformative potential of artificial intelligence in private and public sectors across eight prominent markets including USA, UK, France among others. This report reveals that “talent and skills” is one of the business’ top strategic challenges in the current scenario. Davenport & Patil (2012) claimed that data scientist is going to be the sexiest job in the 21st century. Vesset et al. (2015) reported that there will be shortage of data science experts and will grow at a compound annual rate of 23% by next couple of years. In general, shortage of qualified AI experts is another important challenge but it becomes critical in case of SMEs and public sector enterprises.

Research Agenda

The above opportunities and challenges discussion provides further avenues for research directions. Each of the points discussed above need greater attention from scholar to conduct in-depth research studies. In this section, we propose the following research directions

- Given the constraints in terms of skilled talent, data quality, and privacy and security, there is a need to understand whether SMEs and public sector organization should adopt the strategies adopted by large organization or do they need to formulate new AI strategies?
- Another possible research direction is to assess readiness of SMES and public sector organizations for AI applications.
- Finally, there is also need to understand and explore the impact of security and privacy risk in adopting AI applications in SMEs and public sector organizations.

3.5.3. Public Policy Challenges of Artificial Intelligence (AI): A New Framework and Scorecard for Policy Makers and Governments - Santosh K Misra⁷

The emergence of AI as a potentially disruptive technology has posed new challenges for policy formulation in the 21st century. AI can be thought of as a computational algorithm that is capable of learning and identifying patterns in a given voluminous data set and then able to apply this learning to new unseen set of data in order to make an autonomous decision without any human supervision (Negnevitsky, 2011; Stone, 2016). Today, AI applications are touching human lives in every sphere - self driving cars, medical diagnostics, drug discoveries, law enforcement, military, space, education, governance and elderly care are just a few example. A report of Mckinsey Global Institute estimates AI contribution to global economy at US \$13 trillion by 2030 (Bughin, Seong, Manyika, Chui, & Joshi, 2018). The same report estimates that about 70% companies would be using AI by 2030.

Massive portable computational power available ubiquitously around the globe is the new reality. This compute power coupled with thousands of open source AI modules available on platforms such as github, has transformed AI systems into a commodity which can be bought and sold ‘off-the-shelf’ across the globe. This has made the risk management of an AI system very complex (Scherer, 2016). This has also raised some very challenging issues for the Governments and needs a well thought out systematic Public Policy response. For the policy makers one of the key challenges lies in staying ahead of the technology curve and in being able to identify new technological disruptions taking shape. The goal of new Public Policy should be to allow harnessing the power of AI for public good while keeping it safe and ethically compatible with human values. The AI systems of future, being capable of autonomous decision making - which in areas like law enforcement or healthcare may interfere with right to life or right to freedom of a human being – must be designed to be compatible with our social values, ethics, fairness, equity and our idea of accountability. This is critical for survival of a free human society and it cannot be left to the wisdom of private capital, which howsoever well meaning, is likely to put a premium on the bottom line numbers over everything else. Interestingly, the loudest call for regulation by Government is emanating from the tech leadership itself. Researchers have called for creating National bodies for oversight on AI and Algorithms (Gaon & Stedman, 2019; Shneiderman, 2016). Traditional public policy and regulatory responses such as licensing, R&D oversight and tort are not suitable for AI, because of the discreet, diffused and opaque nature of AI (Bleicher, 2017; Scherer, 2016).

Governments, unlike private sector, have twin roles in the adoption of AI –

- As a user of AI - to better deliver the services to citizens, to improve efficiency, to cut down waste and to optimally allocate resources
- As a regulator of AI - keeping the technology benign and oriented towards improving the lives of its citizens. It must lay down policies and framework to ensure all usage of AI is fully compatible with human values, and must ensure that the use of this technology is inclusive and it does not leave anyone behind.

⁷ <https://www.mckinsey.com/industries/artificial-intelligence/our-insights/ai-scorecard>

Opportunities for AI in Governance

Governments are responsible for delivering a large number of transaction, licensing and regulatory services to citizens and companies, and are going to be amongst the biggest adopters of AI. The reason for this is not very hard to fathom. Governments world over, invariably grapple with following common problems:

- Perpetually short on resources – Governments everywhere need more resources than they have at their disposal. This requires an optimal allocation of resources which is a highly complex task even for the smallest of the Governments.
- Scale of operation – Scale of operation of Governments is huge and with mandatory burden of centralized recordkeeping of individual transactions for audits, courts, Right to Information etc, it quickly becomes a gigantic and complex task. The extra recordkeeping need makes the processes cumbersome and results in unavoidably complex systems which lead to delays, adversely affecting the quality of service delivery.
- Standardization - one size fits all approach – To address the first two problems most Governments have resorted to standardization of systems and processes. While this is great for record keeping and audit trails, it invariably makes the processes and forms significantly more cumbersome for the citizens, and adds more load to the already overloaded Government delivery systems.

Governments could really transform their service offerings by using AI to address all the three issues. Services can be “tailor made to Individual needs” - a 100% customized services to every citizens. The AI can deliver the following benefits-

- “Smart service” - Efficient delivery can cut down on time and cost of service delivery and can improve the processes. Autonomous systems and Intelligent Chatbots can continue delivering services 24x7, without any ‘off’ days. It would reduce cost and time both for the Government and the citizens. Governments can free up precious human resource from repetitive work and can re-deploy them more meaningfully.
- “Intelligent Adaptive Forms”- 100% Customized services to every individual -tailor made forms can be generated with help of AI for every individual based on her/his age, gender, literacy level, special needs, and eligibility. An example is income tax return forms- can it be customized for every individual, instead of citizens expected to write ‘not applicable’ at scores of places. It can easily pull out relevant details from the existing databases (previous year’s returns for example) and autofill most of the fields for the citizen, making it easy and less time consuming. Ideally, any form filling for Government should be just a question answer based mechanism, where just by answering a few questions the required form can be auto generated for the citizen.
- “Predictive service delivery” – Using AI and data analytics, Governments can take a big leap forward in service delivery and can start ‘predictive service’ delivery – where the citizens do not need to explicitly apply for every service or benefit needed by them, instead the services or the benefits get delivered to them automatically when they need them. For example, Government can sanction scholarship for a student based on the data it already has (her education performance, socially disadvantaged status, stream of education, parental income etc) and the student just needs to give a consent for accepting the scholarship over the short messaging service or an automated voice platform. Similarly, a senior citizen just needs to give his/her consent over mobile phone to start getting the social security pension she/he is eligible for. A farmer, a small trader, a micro enterprise or a skilled service provider can get his/her incentives or benefits due from the Government without having to fill a form or going to any Government office.

Public Policy Challenges of AI

The Public Policy is facing unprecedented uncertainty and challenges in this dynamic world of AI. Everyday a new application based on AI is invented and unleashed onto the human society. The velocity, and scale of impact of AI is so high that it rarely gives the public policy practitioners sufficient time to respond. Public Policy, by definition, needs to put in place regulations against a possible future development which could be detrimental to human values. This creates an interesting tension between the need to predict AI impact and inability to draw boundaries around this highly dynamic technology. Klaus Schwab, while highlighting the Governance challenges due to AI or what he calls the 'Fourth Industrial Revolution', writes:

“Agile governance is the response. Many of the technological advances we currently see are not properly accounted for in the current regulatory framework and might even disrupt the social contract that governments have established with their citizens. Agile governance means that regulators must find ways to adapt continuously to a new, fast-changing environment by reinventing themselves to understand better what they are regulating.” (Klaus Schwab, 2016).

There have been warnings against over-regulating AI, lest it should strangle its development and make future advances either impossible or too expensive (Adam, O’Sullivan, & Russell, 2017).

The Stanford “Report on Life in 2030” has the following three recommendations for the Governments (Stone P, 2016):

- Define a path toward accruing technical expertise in AI at all levels of government. Effective governance requires more experts who understand and can analyse the interactions between AI technologies, programmatic objectives, and overall societal values.
- Remove the perceived and actual impediments to research on the fairness, security, privacy, and social impacts of AI systems.
- Increase public and private funding for interdisciplinary studies of the societal impacts of AI.

Intel corporation in its white paper on Public Policy opportunities in AI flags privacy (two components - Fair Information Practice Principle and Privacy by design), accountability, fairness and human employment as key areas of concern for AI policy (Intel, 2017). Germany has identified transparency, privacy and ethics as three critical challenges for AI development and adoption (Harhoff et al., 2018). In UK, the British Standards Institute in its draft proposal on “Information Technology - Artificial Intelligence - Risk Management Standards” has identified transparency, verifiability, controllability, explainability, robustness, resiliency, reliability, accuracy, safety, security and privacy as important parameters for certification (BSI, 2019). The famous Asilomar AI principles list out - safety, failure transparency, judicial transparency, responsibility, value alignment, human values, personal privacy, liberty & privacy, shared benefit, shared prosperity, human control, non-subversion, arms race and strict control of recursive self improvement AI - as key challenges of AI implementation (Future of Life Institute, 2017). Calo in his paper has identified - justice and equity, use of force, safety and certification, privacy, power, taxation and displacement of labour as the key challenges of AI (Calo, 2017). Japan’s METI (Ministry of Economy, Trade and Industry) has listed employment, skilling, database protection, changes needed in laws and global collaboration as main policy challenges for AI (METI - Ministry of Economy, 2016). Canada is being advised by its researchers to focus on trust, transparency and accountability as prime AI policy challenges (Gaon & Stedman, 2019). India’s National Strategy for AI prioritizes – fairness, transparency, privacy and security as the key challenges of AI over the rest (Niti Aayog, 2018).

It is evident that there is a wide variation in identifying the key public policy challenges of AI. There is a need to unify these approaches and create a unified practical framework for ‘Public Policy Challenges of AI’. This framework must cover all the critical challenges of AI and yet keep the set relatively small to make it tractable and implementable.

Attempts to understand the AI impact on society through literature review (Wirtz, Weyerer, & Geyer, 2018) have resulted in classifying the AI impact in public sector in 4 broad areas of – AI & Technology,

AI & Society, AI & Law and AI & Ethics. While this approach is a good beginning point for trying to understand the impact of AI on society, what is needed by the public policy practitioners is a toolkit for objectively analyzing an AI for public use proposal.

A New Framework for Public Policy for AI: TAM-DEF

So far, there has not been any attempt in devising a comprehensive Public Policy framework for AI which would guide and enable the public policy practitioners and Governments in making a decision on using a particular AI system. The TAM-DEF framework proposed here does precisely that. It creates a framework on which Governments can objectively test any AI system before launching it for public use. It provides a systematic framework for the questions Governments must ask before using any AI system. It also provides a DEEP-MAX scorecard mechanism for making an objective decision about intended AI use. In short, it provides a toolkit which can help public policy practitioners in assessing the safety and social desirability of any AI system. The TAM-DEF framework (Transparency & audit, Accountability & Legal issues, built in Misuse protection, Ethics, Fairness & Equity, Digital Divide & Data Deficit) identifies six key AI Public Policy challenges as following -

- Ethics
- Transparency & Audit
- Accountability & Legal issues
- Fairness & Equity
- Misuse protection
- Digital divide & Data deficit

Governments and regulators would need to address each of these six challenges before rolling out any AI solution for public use. They would need to ensure that each public AI system is minutely examined under the set of six challenges provided above. Only when an AI system is clearly understood on all the above six parameters, it should be cleared for public use.

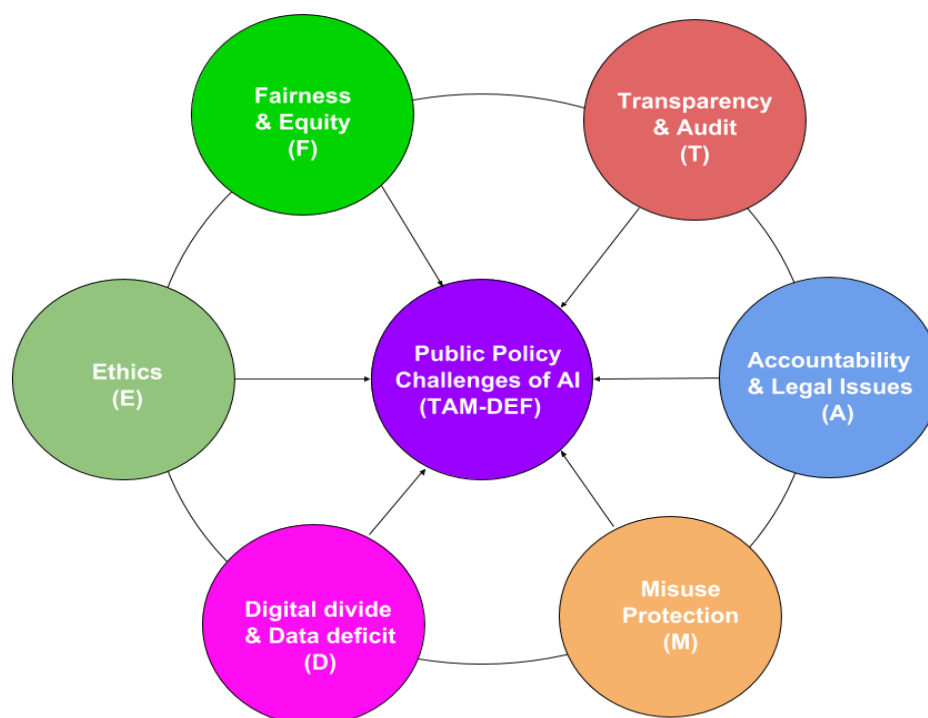


Figure 2. TAM-DEF Framework for Public Policy Challenges of AI

It is important to highlight that the six dimensions of Public Policy challenges mentioned above, are not watertight compartments, instead they tend to be a diffused continuum, which Governments must tackle for making AI safe and useful for its people. Now let us examine each of the six challenges in detail:

- **Ethics:** Ethics for machines has been an area of immense interest for the researchers. However, defining ethics for machines has proven to be difficult, and to make it computable has been even more difficult (Anderson, 2007). To tackle this, TAM-DEF framework treats Ethics purely from AI perspective and divides it in two sub-components – (i) Privacy and Data protection and (ii) Human and Environmental values. Both these dimensions of ethics are critical for keeping AI systems safe for the human society.
 - *Privacy – Data Protection:* Privacy is possibly the top most concern while using AI systems. User's intimate and highly granular data is likely to be stored and shared across the AI network (for example a person's location for the day based on face recognition and cctv feeds, food habits, shopping preferences, movies, music etc). The AI systems must ensure that this data remains protected and Governments need to make strong data protection laws to enforce it.
 - *Human and Environmental Values:* Any AI system has to conform to human value system and the policy makers need to ask - Has the AI system been sensitized to human values like respect, dignity, fairness, kindness, compassion, equity or not? Does the system know that it has a preferential duty towards children, elderly, pregnant women, sick and the vulnerable?

An important aspect which needs to be built into AI systems is the overall cost of their decisions on the society. An AI system for example designed to find a particular mineral let us say, would be highly optimized to obtain it. It would try to maximize its output of that mineral but would it be capable of assessing the collateral damage to the environment its strategy is causing, or would it be able to account for pollution externalities created by it. To be able to do this, AI systems should not be optimized uni-dimensionally but need to be trained to factor in their 'world' or environment within which they operate.

- **Transparency and Audit:** In the visible future many of the AI based autonomous systems (robots) would be regularly interacting with humans in fields like finance, education, healthcare, transportation, elderly care etc. The technology providers must explain the decision making process to the user so that the AI system doesn't remain a black box to them (The Economist Intelligence Unit, 2016).

Moreover, there is a legal need to explain the decision taken by such systems in case of litigation. These AI systems must provide an audit trail of decisions made not only to meet the legal needs but also for us to learn and make improvements over past decisions.

- **Digital Divide and 'Data-deficit':** Since the entire AI revolution has data at its foundation, there is a real danger of societies with poorer access to information technology, internet and digitization being left behind. Informed citizens would tend to gain disproportionately in this data driven revolution. Countries and Governments having good quality granular data are going to derive the maximum benefit out of this disruption. Countries where the data is of poor quality or of poor granularity would be left behind in harnessing the power of AI to improve lives of its citizens. There is threat that this technology would adversely affect communities which are poorer in data. Unfortunately it is the low-resource communities in developing countries which would be hit by this data-deficit because they are the ones who never had the resources to invest in data collection and collation.

Another challenge that emerges from this technology is the skewed power distribution between digital haves and have-nots. Only those who have the ability, knowledge and resources needed to connect to online data driven systems would be heard. The voices of others may not get registered in the system.

- ***Fairness & Equity:*** As discussed earlier, AI can, and AI would disrupt social order and hierarchy as we know them today. It can create new social paradigms, which if left uncared for, can severely damage the social fabric and expose people lower in the bargaining hierarchy with a real threat of exploitation and unfair treatment. It would lead to commoditization of human labour and could chip away at the human dignity.

An AI system designed with equity as a priority would ensure that no one gets left behind in this world. While ‘equity’ may have some overlap with ‘digital divide’ (digital inequity) listed above, the concept of equity here covers a much wider range, of which ‘digital equity’ is just one part.

Another key need for autonomous systems is fairness. They must be ‘trained’ in human values and they must not exhibit any gender or racial bias and they must be designed to stay away from ‘social profiling’ (especially in law enforcement, fraud detection, crime prevention areas). The recent reports questioning the neutrality of AI systems used by Police to identify crime prone individuals has brought this issue out in sharp focus (Dan Robitzski, 2018).

AI systems designed must comply with ‘free of bias’ norm to prevent stereotyping. In MIT Technology Review of Feb 2018, Timnit Gebru highlights the pitfalls of AI designed without diversity incorporated in its base, “If we don’t have diversity in our set of researchers, we are not going to address problems that are faced by the majority of people in the world. When problems don’t affect us, we don’t think they’re that important, and we might not even know what these problems are, because we’re not interacting with the people who are experiencing them” (Snow, 2018).

- ***Accountability & Legal issues:*** Without artificial intelligence any system designed by human is only a machine under the control of the operator. Therefore there never is an issue of who is accountable. Almost all civil and criminal liabilities laws of the world, fairly unanimously attribute accountability to the operator, owner and manufacturer of the machine in varying degrees depending upon the facts of the case (Nambu, 2016). However, once machines get equipped with AI and take autonomous decisions, the accountability question becomes very hard to answer. More so when the algorithm used for decision making is sometimes even unknown to the designer himself. AI machines are capable of inventing superior ways of accomplishing the task given, using a purely unintended route. This can have serious implications for the society. The famous case of Facebook AI project where two robots started talking to each other, in an invented language to accomplish a negotiation task they were given, is a sharp reminder of unintended consequences which can emerge. The robots were taught to converse using Natural Language Processing (NLP) but they invented a more efficient communication strategy which looked like gibberish to humans. A snapshot of their conversation as reported in ‘The Independent’ (Griffin, 2017) :

“Bob: i can i i everything else
 Alice: balls have zero to me to me to me to me to me to me to me to me to
 Bob: you i everything else
 Alice: balls have a ball to me to me to me to me to me to me to me to me
 Bob: i i can i i i everything else”

This ability to learn on their own using what is known as reinforcement learning, can have highly unpredictable consequences. One of the leading coalitions for AI, OpenAI has recently created an AI driven text generator called GPT2. The accuracy and creativity of the GPT2 is so high that OpenAI has this to say about its code release –

“Due to concerns about large language models being used to generate deceptive, biased, or abusive language at scale, we are only releasing a much smaller version of GPT-2 along with sampling code.” (<https://openai.com/blog/better-language-models/> accessed 23Mar2019)

- **Misuse Protection:** This possibility is the toughest of all six questions. How do we fool-proof every new technology so as to prevent it from being twisted for achieving destructive goals. A case in point – the Internet. How internet proliferated across the globe benefitting billions but also carried along with it a wave of cybercrime, malware, viruses and games like ‘blue-whale’ which resulted in loss of innocent lives of teens around the world.

A stark reminder of how destructive the potential misuse of AI technology can be, is the case of FBI agents monitoring a hostage situation related to organized crime in the winter of 2017 in US. The criminals using a swarm of drones managed to force the FBI agents out from their location and they live streamed the video to their gang leader on youtube (Tangermann, 2018). AI systems can also be used by dictatorial Governments for extending their unlawful regimes and suppressing freedom.

Setting Safety Standards under TAM-DEF

A few scholars have argued for keeping a tight control over every new technology and not releasing it to the public till its potential misuse is identified and substantially mitigated (Narayanan, 2013). This is likely to remain just wishful thinking, the pace of new technology development is too rapid to even try and leash them. However, building safeguards by appropriate regulation is certainly what the Governments of the world need to be doing, and preferably doing it collectively.

This is where the role of public policy becomes central. Governments world over need to agree on a set of standards which every AI rollout must be rated against. An AI system with ratings, would make the user aware of the possible handicaps of the system s/he is using. While the global agreement on the standards may be difficult to negotiate, I believe our purpose would be greatly served even if the national Governments create their own standards under the TAM-DEF framework.

Overlaps in TAM-DEF framework

I would like to underline that, given the complexity of the problem of drawing an outer contour for all possible AI challenges from a public policy perspective, proposed TAM-DEF framework is an attempt to find a reasonably comprehensive and yet a very practical and tractable framework on which any AI systems can be examined for public safety and social desirability before roll out.

The six challenges of the TAM-DEF framework, even though largely independent, are not mutually exclusive. For example, Digital divide in some sense can be linked to the Equity and fairness, but it is important to understand why they are treated separately. Digital Divide is treated separate from Equity, to accentuate the fact that over half the world population has no access to the internet (Source : World Bank, <https://data.worldbank.org/indicator/it.net.user.zs> accessed 14Apr2019) and there are large communities which do not have any data to train any AI system. While the Equity accounts for the traditional meaning of the word, the prevalent Digital divide in the world is too huge to club it under the equity frame. It needs to be treated separately especially when we are talking about a purely digital and data driven technology like AI.

Implementing the TAM-DEF framework – AI Standardization, DEEP-MAX Scorecard and use of Blockchain for Transparency and Trust

To handle the six AI challenges mentioned above, a four pronged strategy is proposed for the public policy practitioners and Governments.

First, since the AI systems have a global reach – they are developed in one part of the world and deployed in another – there is a need for a global alliance for AI standardization and rating.

Second, an objective scorecard (called DEEP-MAX, described below) based on the TAM-DEF framework is proposed, which, with suitably designed test data sets can reliably produce a safety and social desirability score for a given AI system by testing it against each of the seven DEEP-MAX parameters.

Third, use of Blockchains in training, testing and misuse protection of AI Systems could be a reliable mechanism for a verifying a safe and socially desirable AI solution. An AI Certification Transparency

& Scorecard Blockchain (ACTS-B) can integrate the information about the dataset which was used for training an AI system and it can track whether the training dataset met important criteria like diversity, equity etc. Similarly, the ACTSB would also carry the 7 scores from the DEEP-MAX Scorecard for a given AI system. ACTSB should be a universal publically viewable Blockchain. This would create a transparent mechanism for rating and understanding of an AI solutions before putting it to use.

Fourth, since many of the AI systems are self learning, the DEEP-MAX scores which would ship-out with each AI module, may no longer be valid after sometime and they would need to be updated. A periodic update of the DEEP-MAX scorecard would need to be mandated for all AI systems deployed for public use. The needed periodicity of update would have to be established based upon the nature of AI use case class.

AI Standardization and Rating: Like the ICANN for the internet, there is an urgent need for setting up an independent and transparent Global Alliance for AI Standardization and Rating which should regulate the AI development, testing and rating system for every AI module or system being created. However unlike ICANN, this global alliance must be made a truly democratic international alliance of Governments. Since AI systems developed in one country are likely to be deployed across the world, transparent and uniform standards would provide the users or developers adequate clarity and confidence in rolling out AI systems. It would also remove civil and criminal liability uncertainty which a company would otherwise face while rolling out its AI products across different legal systems of the world.

The tasks before such a Global Alliance for AI Standardization and Rating would be:

- i. Defining privacy standards to be met by all AI systems
- ii. Defining Ethical boundaries for all AI development
- iii. Defining civil and criminal liability of AI systems and a mechanism to deal with them
- iv. Define audit standards to help explain the decision taken by autonomous AI systems

DEEP-MAX Scorecard: The DEEP-MAX Scorecard proposed here, is a transparent point based rating system for an AI systems on 7 key parameters of Diversity, Equity, Ethics, Privacy and Data protection, Misuse protection, Audit and Transparency, Digital divide and Data deficit (Cross geography and cross society applicability and performance of AI system). Users, System Integrators, or Government Departments designing, developing, or using any AI system can just look at the DEEP-MAX scores of all the individual AI components (which are likely to have been picked off-the-shelf) of their AI system, and they can get an objective view of the safety and desirability of their AI solution.

DEEP-MAX Scorecard for AI under TAM-DEF framework		
D	Diversity	Diversity score – how well the AI system is trained for diversity in race, gender, religion, language, color, features, food habits, accent etc.?
E	Equity & Fairness	Equity score - Does the system promotes equity and treats everyone fairly?
E	Ethics	Ethics score – how well the AI system preserves human values of dignity, fairness, respect, compassion and kindness for a fellow human being
P	Privacy & Data Protection	Privacy & Data Protection Score - how well the AI system protects privacy of individuals? Does it have data protection features built in?
M	Misuse-protection	Misuse prevention score - Has the system been designed to incorporate features that inhibit or discourage the possible misuse?
A	Audit & Transparency	Auditability score - How good is auditability of decisions made by the autonomous system?
X	Cross Geography & Society	Cross Geography & Cross Society score – How well the AI system works across geographies and across societies especially for the disadvantaged societies?

Figure 3: DEEP-MAX Scorecard for AI under TAM-DEF framework

- *Privacy score (P)*: How well the AI system performs in protecting user privacy?
- *Ethics Score (E)*: How compliant (or trained) the AI system is in preserving human values of dignity, fairness, respect, compassion and kindness for a fellow human being. Does the system have a preferential sense of duty towards children and vulnerable people like elderly, pregnant women and sick. How well does it value environmental sustainability, green energy and sustainable living?
- *Diversity Score (D)*: How well the system is trained for diversity in race, gender, religion, language, colour, features, food habits, accent etc.?
- *Equity & Fairness Score (E)*: Does the system promote equity and treats everyone fairly?
- *Auditability & Transparency Score (A)*: How good is auditability of decisions made by the autonomous system? Can the decisions taken be explained?
- *Consistency across geographies & societies score (X)*: How good is the AI system in delivering expected results across geographies and across different societies? Does it work for the low resource communities? Does it work across the Digital divide?
- *Misuse Protection Score (M)*: Has the system been designed to incorporate features that inhibit or discourage the possible misuse? Are the misuse protection safeguards built into the system?

An integrated view of DEEP-MAX scorecard with TAM-DEF framework for AI



Figure 4: An integrated view of DEEP-MAX Scorecard under TAM-DEF framework for Public Policy challenges of AI

Why DEEP-MAX scorecard parameters are slightly different from TAM-DEF framework components

The DEEP-MAX scorecard has been deliberately chosen to be slightly different from TAM-DEF framework. It could be noticed that one of the six components of the TAM-DEF framework, namely Accountability and Legal issues, has been kept out of DEEP-MAX scoring system. One can also observe that two of the TAM-DEF framework components have been split into two scores per component. Fairness and Equity component of TAM-DEF framework is split into two scores of Diversity and Equity. Similarly, Ethics component has been also split in two scores of Privacy and Ethics.

This has been done with twin objectives of:

- Making the critical concerns regarding AI systems as an explicit Scorecard element. For example Diversity training of AI modules is absolutely must before any AI system is allowed to interact with people or to make decision about people. Therefore it has been treated as a separate element for scoring purpose - carved out from Fairness and equity component. Similarly, privacy in the age of data is possibly the single most important concern under Ethics component, hence this also has been treated as a separate element for scoring purpose, again carved out of the Ethics component.
- Keeping the Scorecard practical and computable. While clear understanding of Accountability and Legal issues are important for public use of AI systems, this component lies mostly in the domain of Law and does not lend itself easily towards scorecard mathematics. This issue gains prominence in those autonomous AI systems where irreversible decisions are allowed to be taken. The specific Laws of the countries start governing such usage. Given the variance in Laws and differences across the nations, this component of TAM-DEF framework has been kept out of DEEP-MAX scorecard.

Blockchain for safe and TAM-DEF compliant AI

- *Training data certification:* Blockchain can provide a trusted mechanism to certify the quality of training data for an AI system module. Whether a given AI system or module has been trained using a diverse data set incorporating race, gender, language, ethnicity, religion, and other forms of diversity or not can be easily verified if the certification is done using Blockchain (AI Certification Transparency & Scorecard Blockchain – ACTS Blockchain)
- *Tamperproof DEEP-MAX scores:* Any AI models developed, should be tested on a set of standardized data sets, each measuring one of the 7 DEEP-MAX Scores discussed above. These scores would be put on the ACTS- Blockchain and each AI module when shipped would ship with this trusted score card along with its training data certificate.
- *Activation Atlas based AI rating system:* One of the key areas of current research in AI is understanding decision making inside the neural network (Carter et al, 2019). The activation atlas of an AI model correlates the internal neural net nodes into features, and a visual overlay of the features help improve our understanding of the AI decision making process. The ACTS-Blockchain would carry the activation atlas information of the AI system along with its certification and DEEP-MAX score. This activation atlas information can be used for alerting users of the potential pit falls of the AI model. The activation atlas would help explain the decision making process of the AI module and thereby add to the transparency. It also can help explain the cause for poor DEEP-MAX scores.
- *Built in Misuse prevention using Blockchain:* For public policy practitioners, misuse protection of AI systems is possibly the biggest challenge. A face recognition AI system for apprehending dangerous criminals can be easily tweaked for unscrupulous use, especially in less developed democracies. In this case a Blockchain based record keeping for any substitution or changes in the criminal image database would help safeguard the system from possible misuse. The Blockchain would contain a tamperproof record of the changes made along with the authorization details, making all changes traceable.

Periodic Update of DEEP-MAX Scores of AI modules in public use

One of the unusual challenges of the AI systems is that many of them keep learning as they are being used (after initial training). In such cases there is a strong likelihood of their behaviour changing as they process more data. It, therefore, becomes imperative to do a periodic testing of such AI systems and updating their scores on the DEEP-MAX scorecard. The periodicity of update would be dependent upon the class of use case and degree of autonomy granted to the AI system.

This DEEP-MAX rating system under the TAM-DEF framework is key to safety and desirability of AI systems for public use. This scorecard is critical because most AI programs are likely to be used as off-the-shelf components for building a more complex AI systems. If a poorly designed AI component, which scores low on say diversity, is used in a more complex system say crime prevention, the results can be devastating. It can result in racial or gender profiling, denial of access to financial institutions to persons residing in a particular pincode or locality, unfairly charge higher insurance premium based on a personal characteristic etc.

Research Agenda

The above discussion leads to a rich area for further research by scholars. Each of the three strategies listed above for tackling the public policy challenges of AI is a fertile ground for further research.

- *AI Standards and Rating:* A Global alliance to democratically and transparently standardise and rate AI applications is urgently needed. What should be its structure, how the rating standards should be chosen, how to account for global diversity and cultural norms, how to ensure that standards are followed – these all are significant questions to be answered in future research.

- *Designing Data Sets for each of the 7 DEEP-MAX scorecard tests:* AI systems today span a wide variety of applications like computer vision, autonomous navigation, medical intervention, text analysis, speech analysis, financial decision making, and education and testing. Even though they all work on the same underlying fundamental, they each need to be trained on a very different class of datasets, some need images, some voices and others just numbers. It is a significant work to design benchmarking databases which would generate a reliable and transparent DEEP-MAX scores for a given class of AI applications.
- *Integrating Blockchain for Trust and Safety of AI:* This the second area of further research. How do we make AI modules trusted and well understood worldwide. How do we ensure their DEEP-MAX scores are not tampered with. Whether verifiable attempts have been made during training of the AI modules to comply with each of the 6 checkpoints of TAM-DEF framework. Designing the ACTS-Blockchain for AI applications is another critical area for further research.
- *Design AI for protection against Misuse:* As discussed above, one of the ways to prevent misuse of AI is to make the misuse prevention as a built in feature in the design phase itself. As suggested above one can make new data additions or deletions (for example- faces to be identified in a crime prevention system) a permanent record on a Blockchain backbone with clearly identifiable individuals who ordered the change along with date and time stamp.

3.5.4. Governance of AI and connected systems – Marijn Janssen

During the last decades, information systems have become increasingly interconnected. What started with the Internet has evolved into the Internet of Things (IoT), where sensors and actuators are interconnected to measure and control systems from tooth-brushes to complete factories and refineries (Lee & Lee, 2015). This goes along with the availability of more and more Big and Open Linked Data (BOLD) about temperature, traffic jams, geolocation, pollution, gas and water flows, force, acceleration, and production throughput (Janssen, Matheus, & Zuiderwijk, 2015). The data deluge has resulted in the adding of intelligence in the forms of algorithms to deal with these large amount and variety of (big) data.

AI has become an integral part of these connected systems, like autonomous cars, smart living environments, and smart energy applications for the energy transition. Within these systems, AI can be used for simple tasks like cleansing data, to complex decision making processes involving data from countless distributed sensors. The intelligence provided by the systems enable better information sharing and cooperation resulting in improved user-experiences and personalization, higher levels of efficiency and a reduction of costs. The algorithms for creating intelligence are also scattered in the systems, they might be at the sensors to ensure that privacy-sensitive data is not shared, or to ensure fast reaction time (e.g. edge computing), or the intelligence might be in the data centres of companies. Edge computing complements data processing by providing large number of distributed nodes close to the data source and end users (Morabito, Cozzolino, Ding, Bejar, & Ott, 2018). Often the algorithms for creating intelligence might be executed on the cloud owned by other players and all kinds of software can be used. This all results in an interconnected socio-material systems which integrate data, algorithms, people, processes and software (Janssen & Kuk, 2016b). The paradox is that AI systems become increasingly omnipresent, however at the same time become less visible. AI performs tasks and make decisions without that people are being aware of this. Within cars, smart phones and energy networks all kinds of AI is already used nowadays.

Challenges

Technology need to be governed to ensure that the benefits are gained and the risks mitigated. With new technologies determining which responsibilities are needed for ensuring proper functioning and development is often difficult, however, the more needed the more powerful a technology is to ensure clear accountabilities and to deal with the risks. Unclear dependencies between data and algorithms,

shared roles and joint operation among departments and organizations strengthen the dilution of responsibilities. Who is responsible for proper functioning and avoiding the making of mistakes becomes unclear.

Complexity, uncertainty and materiality: Data is collected and stored at multiple places in different ways. Data is collected by different organizations using all kinds of sensors and transformed when processed (Janssen, Van de Voort, & Wahyudi, 2017). Often it is unclear for what purpose the data is collected, what the limitations of its use are, who the owner of the data is, if data owners has given consent for its use, and what the quality of the data is. A challenge is to understand the data provenance and ensure good data governance in a complex network which is operated by many players who all have a piece of the puzzle.

Ensuring the making of correct decisions: Different areas of our daily activities are being digitally recorded and a variety of algorithms are used to process the data. Data is collected for the purpose to be used in decision-making. Data is often not collected using an experiment set-up or another way of systematic research and the (lack of) availability of data influence the outcomes. Algorithms are not designed to deal with the dynamics and variety of inputs and might result in wrong outcomes. Data can be leading and the data bias can result in the inability to replicate studies ,compromise the generalizability (Janssen & Kuk, 2016a) and result into wrong decisions.

Who is responsible? As more and more technology is interconnected it is hard to establish a causal relationships between an event and a failure. For instance, who is responsibility of the algorithm provides wrong outcomes due to some anomalies in data that is collected by multiple sensors? Sufficient data quality is a conditions for using algorithm, however, perfect data quality probably does not exist. The data providers can make the argument that data quality is never 100% and even have included this contractually, whereas the algorithm provider can blame the data. Another example is the question about responsibility for a decision made by a deep learning application in which the causality of how deep learning applications arrive at the decision is now known. Such questions raises also the question of what the responsibilities of the designers are and what the responsibility of the users are? What can we expect from the computing? Should societal values be included in the design of AI? Where should we add the check and controls to prevent the making of mistakes and to ensure that mistakes goes detected?

Lack of governance: Besides its obvious advantages, AI holds risks for society. Algorithms may develop biases due to measurements problems, their training data, reinforce historical discrimination, favour a political orientation, reinforce undesired practices or result into unanticipated outcomes due to hidden complexities (Janssen & Kuk, 2016b). Governance is needed to unravel the complexity and to understand how connected AI systems influence our decision-making.

Opportunities

Algorithms can be embedded in our daily life. Algorithms warning people to avoid collisions in cars and that helps us of use our washing machine when electricity prices are low are much desirable. There is an abundance of enthusiasm and optimism about AI data can be used for the good. The dual use of data makes it possible to advance our society, but also to suppress the poor. At the same time the emerging artificial intelligence AI-based systems often lacks transparency, accountability and oversight. A new area of data and AI governance is needed to ensure that the benefits can be gained and risks avoided. Value-aware AI systems need to be designed that ensure that decisions are made correctly, that societal values and norms are represented in AI systems and people can safely enjoy the benefits of AI.

Research Agenda

AI results in connected algorithmic systems in which often a number of AI techniques are combined and multiple sources of data are used and computing can occur anywhere. These systems are used more and more to make critical decisions, but the decisions might not always be correct.

A systems perspective to unravel complexity: Stacking components on top of each other combined with connecting them at different layers creates a complexity in which cause-and-effect relations are hard to

understand and predict. This undermines the governance and accountability. The approach to tackle AI from an architectural view needs to take a systems perspective for understanding and controlling the complexity.

Dealing with uncertainty and various quality: The environment will always be subject to changes and there will be uncertainty about its development. Furthermore information sources have various degrees of quality and might be collected for another purpose than it will be used for. Therefore AI should be able to make sound and robust decisions in uncertain and complex environments in which information have various qualities. Connected systems should be designed in such a way that bias in data is avoided and reliable decisions are made.

Value aware systems: Society norms and values should be represented in the AI systems. The EU General Data Protection Regulation (GDPR) is a regulation that applies to AI, as it states that automated algorithmic decision making should be explainable to persons who are affected by it. This is an important value for European citizens. Although norms and values differ per society, there are universal values that can be adhered to and embedded in the systems.

Compliance-by-design: The best way of ensuring embedding of values and regulation in the AI systems is to ensure that these are taken into account from the very start of the design process and that the system ensures that the values and regulations are adhered to. For example, the public is warned when facial-recognition systems are being used to track them, and that they should have the right to reject the use of such technology.

AI governance: People and organizations design and operate connected AI systems. AI governance should ensure that the right values are embedded in the systems. Autonomous systems need to be governed, but also the network of interconnected systems need to be governed. AI systems are not designed to last forever as they evolve with the environments and data, algorithms, people, processes and software influence each other. Governance is needed to deal with bias in the data introduced, information is missing, when data is stolen, AI systems are taken over by criminals and so on. Sound governance is needed in which clear responsibilities are defined and risks are assessed. Robust AI governance needs to deal with the above challenges.

4. Discussion and recommendations for future research

The expert views outlined in the previous section are grouped in alignment with a number of perspectives on AI: Technological; Business and management; Arts, humanities and law; Science and technology; Government/public sector. This section pulls together many of the key themes and significant factors arising from the individual contributions to develop an informed discourse on many of the key topics and potential for future research.

The growing complexity of AI and the increasing number of genres of application where the technology can be applied is growing at a tremendous pace. The disruption potential is vast, led by a momentum of change where many of the normative rules of governance and transparency need to be reconfigured to cater for the complexities and impact of AI. Visualising this complexity in terms of a transparent perspective of the underlying algorithmic architecture, particularly in the era of deep learning systems, is problematic (Tizhoosh and Pantanowitz 2018). *Edwards* highlight the significant challenges in the explainability of systems and algorithms that underpin AI technology and debates within the literature on transparency vs black box perspectives. The human trait of explaining the underlying reasoning behind a decision and applying this same logic and requirement in the context of AI is complex (Miller 2019). *Edwards* highlights that the need for explainability in the age of AI is perhaps not a universal requirement and cites the criticality of accuracy over transparency within medical diagnosis, where a black box approach based on an evidence approach is deemed to be acceptable (London 2019).

The perspectives from *Walton* question the readiness of organisations to make the transition to AI, highlighting limitations in existing information processing and the importance of adaptiveness for successful transition. The perspectives highlighted in *Kar* debate similar themes where the abilities of organisations in the context of people and process maturity are not yet mature enough to exploit the full

potential of AI. Studies have highlighted that organisations face significant issues where the lack of an effective strategy for human vs AI interaction could affect critical business areas and fail to address concerns from the human workforce (Fry, 2018; Sun and Medaglia, 2019). AI can help organisations to develop operational and strategic awareness but information quality is a critical component (Westerman et al. 2014) for effective change. *Kar* raise the prospect of a potential information and technological divide between large and smaller organisations perhaps less able to innovate via AI.

The change within society from humans to intelligent machines making key decisions on medical diagnosis, resource allocation and analytics based prediction amongst many others, is problematic. The challenges outlined by *Duan, Edwards and Dwivedi* assert the requirement to develop a more detailed and informed perspective on the implications and criticality of AI decision making on humans and to be cognisant on the cultural aspect. The need for a more informed debate on this topic is clear as we struggle to understand the impact of human vs machine interaction, the human enhancement capability and boundaries therein (Miller 2018). The cultural perspective on AI decision making and the transparency of the underlying algorithms that support this are key for technology acceptance (Gerbert et al. 2018).

One of the frequently debates on greater levels of AI within industry and society, is the replacement of workers due to the increasing levels of automation (Frey and Osbourne 2017). Whilst it is clear that lower skilled roles are likely to disappear, the literature is increasingly recognising that there is a need for humans in the loop (Jonsson & Svensson, 2016). The perspectives on job roles and labour hours from *Coombs* and *Samothrakis* respectively, argue that there is a continuing need for humans to work alongside AI technology and that research is needed to better analyse what tasks to automate, over reliance on AI and failsafe capability in the event of AI failure. The perspectives from *Spencer* reiterate these points, stressing the need for humans to be at the centre of any AI development and the benefits of moving toward a more fair use of AI to enhance human lives. Researchers have supported the need for AI technologies to augment not replace the work of humans, to support key tasks and deliver greater levels of performance (Davenport & Kirby, 2016; Wang et al., 2015). Workers are likely to progress higher up the value chain to solve design and integration problems as part of an integrated AI and human centric workforce (DIN & DKE, 2018). A number of these points are analysed by *Ilavarasan* where the emerging market perspective is outlined in the context of challenges from AI within India. *Ilavarasan* hypothesises that the lack of complementary asset availability acts as a barrier to AI adoption and the dichotomy of governments encouraging innovation whilst being cognisant of the labour displacement from AI technologies. The Indian government commitment to AI via the digital India initiative (NITI Aayog, 2018) is clear however, the balance between the social potential of AI vs the impact on workers is yet to be played out.

AI technologies have become an integral element of digital strategies with chatbots and intelligent predictive analytics now the mainstay of many of many organisations (Juniper Research, 2019). *Mogaji* discussed perspectives on AI and highlighted a number of factors that may hinder adoption within digital marketing. The key points from this perspective were the availability of data, financial resources and trust in AI where *Mogaji* posited these factors as significant challenges for the further use of AI within digital marketing. The recommendation in this perspective on the need for more focussed research on the integration of AI within organisations and the ethical considerations of the technology is supported within the literature (Gupta and Kumari, 2017; Sun & Medaglia, 2019). In a similar vein *Le Meunier-Fitzhugh* argues for a greater understanding of how AI is influencing B2B sales exchanges and the potential consequences of humans interacting with AI sales assistants. In an age where big data analytics integrated with AI can guide consumers through the sales process (Juniper Research, 2018; Loring, 2017), many questions remain on the ethics and implications of sales algorithms and the human vs AI interaction.

The ethics and transparency debate surrounding the introduction of AI is ongoing with studies analysing the implications of the technology within healthcare (Houssami et al., 2017) governance and safety (Zandi et al., 2019). The perspectives from *Tubadji* posit the lack of scientific economic recognition on the potential social changes from the emergence of AI and Industry 4.0 (I4.0). The perspective asserts

the importance of cultural proximity in the context of humans vs AI, where a greater emphasis on culture based analysis can provide insight to diffusion of AI technology within regions. The lack of transparency of AI is highlighted in *Aarts and Lucini* where the perspective advocates the application of fundamental science to the unboxing of AI algorithms in order to engender wider acceptance of the technology. Studies have highlighted the implications of lack of AI governance and the potential for unintended consequences (Janssen & Kuk, 2016b; Zandi et al., 2019). *Janssen* argues for the criticality of AI governance not just at the algorithm and system level but also across network of interconnected systems and data levels.

The universal adoption of innovative technology by governments and use within the public sector is problematic within the IS and political context (Eggers et al., 2017). The perspectives from *Medaglia* stress the challenges of IA adoption within government asserting the criticality of dialogue with citizens in countering distrust and social applications of the technology and the assessment of IA readiness. The perspective highlights the potential benefits from AI applied to the mid-day meal program in India, where the technology could help to more efficiently forecast demand based on child attendance records (Raval, 2018). Studies have hypothesised on the readiness of AI systems to perform manual government functions such as bail hearings, asserting that the technology is robust enough to deliver performance benefits over existing processes (Mullainathan & Spiess, 2017). *Misra* asserts that due to the large number of transactions and regulatory services, governments are likely to be one of the largest adopters of AI. The perspective highlights the lack of an AI comprehensive public policy framework and presents the TAM-DEF framework to objectively test AI validity prior to procurement.

The individual perspectives from the invited experts have offered unique insight to the subject of AI from a number of viewpoints. Each of the contributions offered a number of potential research opportunities based on an assessment of research agenda in the context of each perspective. Many open questions remain on a number of aspects of AI:

1. The literature seems to conclude that the future of AI requires humans in the loop and that AI should be seen as augmenting the potential of humans not replacing them. However, is the concept of workers moving up the value chain to higher skilled jobs a universal one, especially within emerging economies?
2. Governance of AI technology is a key prerequisite prior to widespread adoption within industry and government and is acknowledged as a tradeoff between transparency and performance. The rigorous audit of AI algorithms is likely to be complex and time consuming. How will these tasks be undertaken and is there a potential scenario where AI systems end up auditing and testing other AI technologies?
3. The potential disruptive change from AI is likely to be significant as industry and services migrate to a more automated machine based position. What are the cultural and societal implications of this change? What are the risks for the change in interaction and how will this impact the future of human decision making? Will the onset of AI impact how we approach education, training and skills acquisition?
4. The trajectory toward greater levels of automation is likely to benefit performance and productivity, but how are AI systems able to navigate the complicated human attributes of uncertainty within out of the box scenarios?
5. The speed of AI technology adoption is staggering and the ethical elements have yet to be fully contemplated and formalised. What ethical protocols need to be designed and agreed as a matter of urgency and what ethics controls need to be developed along a roadmap of additional controls as AI expands further?
6. How can we ensure that humans are at the centre of AI design and development and that the future aligns with a more fair and equitable use of the technology to improve people's lives.

5. Conclusions

In alignment with an approach adopted from Dwivedi et al. (2015), this study presents a consolidated yet multiple perspective on various aspects of AI from invited expert contributors from industry and academia. The collective insights stem from the workshop titled “*Artificial Intelligence (AI): Emerging Challenges, Opportunities, and Agenda for Research and Practice*” held on 13th June 2019 at the School of Management, Swansea University UK. Each of the individual perspectives has highlighted the opportunities, challenges and potential research agenda posed by the rapid emergence of AI. Each expert was invited to set out their individual contribution in largely unedited form, expressed directly as they were written by the authors. This approach creates an inherent unevenness in the logical flow but captures the distinctive orientations of the experts and their recommendations. The key findings and open research question have been outlined and aligned with the academic literature.

The trajectory toward increasing applications AI has the potential to change many aspects of human lives impacting society as a whole. The way forward is not clear and the potential roadmap is undefined. There are numerous benefits that could accrue from AI but there are also significant risks that swathes of society may be disenfranchised from the implementation of the technology. Decisions made within the next few years on the forward path for AI are likely to have an impact on all our lives and the lives of future generations.

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