Preface

Historically, research and development work concerned with intelligence has been anthropocentric. This is an extreme form of speciesism, which involves human beings considering human beings as superior to all other life. This can lead to erroneous assumptions about, for example, tiny brains being capable of only tiny intelligence, or no brains equalling no intelligence. Yet, insects with tiny brains have complex behavioral repertoires comparable to those of any mammal. For example, a honeybee's brain weighs only about one milligram, but honeybees can count, differentiate, and categorise. Furthermore, plants do not have centralized brains, but they are capable of communication and other intelligent behaviours. Unlike human beings, plants can survive and function even after losing 90% or more of their mass. Thus, plants have no centralized brains because that would make them vulnerable – not because plants do not have intelligence. Moreover, even tiny and brainless lifeforms can exhibit formidable problem solving capabilities as they compete with human beings. For example, bacteria can exhibit formidable microbial intelligence as they adapt to survive and prosper against the onslaught of human-made pesticides and pharmaceuticals intended to eradicate them.

Anthropocentric perspectives have been of limited usefulness in research as they overlooked the capacity of many different lifeforms to handle complex challenges through intelligent behaviours such as self-awareness, association and anticipation, decision-making, and robust adaptation. Furthermore, anthropocentric perspectives have been of limited usefulness in development as attempts to mimic human general intelligence led to little progress in artificial intelligence for decades. By contrast, research and development that has sought to go beyond anthropocentric perspectives has been much more fruitful. In particular, intelligence research with post-anthropocentric perspectives has revealed formidable capabilities of microbial intelligence and plant intelligence, as well as insect intelligence, avian intelligence, and the intelligence of many other animals. At the same time, the development of AI has advanced rapidly through harnessing insights from post-anthropocentric research, while seeking to introduce many AI applications that have their own specific narrow focus – rather than general intelligence. As the range of natural intelligences becomes apparent and the range of artificial intelligences increases, it is appropriate to consider how the many different natural and artificial intelligences can be combined effectively in hybrid systems and hybrid beings. Accordingly, multi-intelligence hybrid systems and hybrid beings is the topic of this report.

Contents

Abstract

1. Introduction

The topic of this report is multiple intelligence hybrid beings and hybrid systems. This goes beyond extant research and practice in related fields such as, for example, swarm intelligence. The following types of intelligences are considered: natural (human, canine, avian, insect, fish, plant, microbial) and artificial (self-awareness, association and anticipation, decision-making, robust adaptation, problem solving). For purposes of exposition, various examples are provided of historical, present, and potential multi-intelligence hybrid systems and hybrid beings are provided as follows: natural intelligence + natural intelligence; natural intelligence + AI; AI + AI. Subsequently, initial principles are set-out for research, development, and innovation work focused on multi-intelligence. Then, directions are proposed for future research, development, and innovation. These encompass metaphysics, socio-technical theory; semiotics; and systems engineering.

2. Types of intelligences

First in this chapter, brief summaries are provided of the following different types of natural intelligence: human, canine, avian, insect, fish, plant, and microbial. Clearly, these are not all the types of natural intelligence. Rather, these brief summaries provide comparative examples of natural intelligence, which inform later sections of this report. Second in this chapter, brief summaries are provided of different aspects of artificial intelligence as follows: self-awareness, association and anticipation, decision-making, robust adaptation, and problem solving. Again, these are not the only possible ways of considering aspects of artificial intelligence. Rather, the brief summaries provide examples to inform later sections of this report.

2.1 Natural intelligence

2.1.1 Human

Compared to other intelligences in nature, human intelligence is the most researched. This includes outputs, processes. With regard to outputs, IQ (intelligence quotient) scores are derived from intelligence tests. Some IQ tests aim to measure general intelligence (g), and encompass mathematical skill, verbal fluency, spatial visualization, memory retrieval, and reasoning approaches. However, rather than measure general intelligence, IQ tests may measure outcomes arising from access to relevant education and/or behavioural, motivational and social factors (Flynn, 1987; Bandura, 1993; Neisser, 1997; Seligman, 1992). Notably, as IQ scores have risen over generations, creativity quotient (CQ) has fallen. This had led to claims of there being a “creativity crisis” (Powers, 2015). These trends could be related to distinctions between processes in fluid intelligence and crystallized intelligence. Fluid intelligence is the capacity to identify patterns, reason and solve novel problems, independent of any knowledge from the past. By contrast, crystallized intelligence is the ability to use skills, knowledge, and experience, drawing upon long-term memory. It is argued that these can be separate neural and mental systems, but are correlated with each other (Cattell, 1963; Geary, 2005).

More generally, there are numerous opinions about what measures of human intelligence should encompass. For example, it has been argued that intelligence involves processes that are linguistic, logical, spatial, musical, bodily-kinesthetic, interpersonal, intrapersonal (Gardner, 1993). Others have argued that different types of different people’s intelligence can be categorized more simply in terms such as realistic, investigative, artistic (Ackerman, 1996) or analytical, creative, and practical (Sternberg, 1985). With regard to processes, it has been argued (Das, 2002; Luria, 1966) that human intelligence involves four processes (planning, attention, simultaneous, successive) related to brain areas (frontal lobe, lower cortex, occipital and the parietal lobes frontal-temporal lobes). Others have argued that proposed that the biological basis of intelligence stems from how well the frontal and parietal regions of the brain communicate and exchange information with each other (Deary, Penke & Johnson, 2010; Jung & Haier, 2007). Fundamental studies across species relate human intelligence to emergent behaviours related to self-awareness, association and anticipation, decision-making, robust adaptation, and problem solving (Westerhoff, 2014).

2.1.2 Canine

Research into canine intelligence has included studies that use measures of human intelligence outputs (Coren, 2009), and other studies investigating more fundamental aspects of intelligence such as self-awareness (Ardena & Adams, 2016). Research findings indicate that dogs learn quickly from each other. For example, puppies learn behaviors quickly by following examples set by experienced dogs. Domestic dogs have more advanced social-cognitive abilities than dogs’ closest canine relatives, and indeed mammals such as great apes. Rather, their social-cognitive abilities parallel some of the social-cognitive skills of human children (Tomasello and Kaminski, 2009). The cognitive capacities of dogs have inevitably been shaped by millennia of contact with humans (Hare, 2002). As a result of this physical and social evolution, many dogs readily respond to social cues common to humans and quickly learn the meaning of words (Kaminski et al, 2004).

However, domestic dogs may have lost some of their original cognitive abilities once they joined humans. For example, dingos can outperform domestic dogs in non-social problem-solving experiments and, more generally, domestic dogs can call upon human beings to solve difficult problems for them (Udell et al, 2010). It has been argued that some breeds of domestic dogs, such as border collies, exhibit higher levels of intelligence than others (Coren, 2009), and that there can be much variation of intelligence within one breed (Coren, 2016). A study published in the scientific journal, Intelligence, indicates that domestic dogs have overlapping cognitive abilities. This finding was derived from a study assessing individual differences in cognitive abilities in 68 border collies to determine the structure of intelligence in dogs. It was found that dogs quickly completing a detour tasks also tended to score highly on a choice tasks; and his could be explained by a "g" (general intelligence) factor (Ardena & Adams, 2016).

2.1.3 Avian

Avian brains are separated from those of mammals by some 300 million years of independent evolution. Hence, avian brains are structurally very different from the brains of mammals. Nonetheless, they have the neural circuitry associated with higher-level consciousness (Butler et al, 2006; Butler et al. 2005). Not least, research suggests that birds have the ability to attribute mental states to themselves and to others, while understanding that others have different mental states (Watve et al, 2002). In practice, birds learn from each other and are adept at making and using tools (Bugnyar & Kotrschal, 2002; Emery, 2006; Gentner et al, 2006).

Bird communication can be remarkably sophisticated. For example, some birds can use the perception and learning capabilities of embryos to alter their offspring's developmental trajectories. For example, zebra finch parents can acoustically signal high ambient temperatures (specifically above 26°C) to their embryos. Exposure of embryos to these acoustic cues alone adaptively alters subsequent growth in response to nest temperature and influences individuals' reproductive success and thermal preferences as adults (Mariette & Buchanan, 2016).

2.1.4 Insect

Insects can navigate over long distances, find food, avoid predators, communicate, display courtship, care for their young, and so on. Ants use a variety of cues to navigate including, such as sun position, polarized light patterns, visual panoramas, gradient of odors, wind direction, slope, ground texture, and step-counting. Overall, the list of cues ants can utilise for navigation is probably greater than for humans. However, ants do not integrate all this information into a unified representation of the world, a so-called cognitive map. Instead they possess different and distinct modules dedicated to different navigational tasks. These combine to allow navigation. One module keeps track of distance and direction travelled, and continually updates an estimate of the best "bee-line" home. A second module, dedicated to the learning of visual scenery, allows ants to recognise and navigate rapidly along important routes as defined by familiar visual cues. Finally, ants possess an emergency plan for when both of these systems fail to indicate what to do: in other words, when the ant is lost. In this case, they display a systematic search pattern.

Ants can keep track of the direction they have just been travelling, allowing them to backtrack if they unexpectedly move from familiar to unfamiliar surroundings. Evolution has equipped ants with a distributed system of specialised modules interacting together. In particular, the navigational intelligence of ants is not in an ability to build a unified representation of the world, but in the way different strategies cleverly interact to produce robust navigation (Chittka & Muller, 2009; Chittka & Niven, 2009; Chittka & Skorupski, 2011; Wystrach, 2013).

2.1.5 Fish

Fish have many of the cognitive powers associated with intelligence (Brown, 2004). Fish can learn different skills in different ways, including through social learning (Reader et al, 2003). Fish can use tools (Pasko, 2010), build (Clark et al. 1998), hunt (Schuster, 2006), avoid capture, escape from nets (Czanyi & Doka, 1993), and avoid being killed (Foster, 1988), in some cases by feigning death (Tobler, 2005). When they are not building, hunting, or avoiding harm, fish can past time by playing (Helfman & Collette, 2011).

For example, some types of wrasse use rocks to crush sea urchins in order to eat their softer insides, while cichlids and catfish have been observed gluing their eggs to leaves and small rocks, which they carry around when their nests are disrupted. (Brown, 2015; Gertz, 2014; Greenwood, 2014).

2.1.6 Plant

If intelligence is the ability to solve problems, then plants are highly intelligent. For example, many plants turn to the sun to meet their energy needs. This can include plants growing through shady areas to locate light, and turning their leaves during the day to capture the best light. More than 500 types of plants meet their energy needs by preying on animals ranging from insects, rodents and even birds. To make this possible, plants have evolved complex lures and rapid reactions to catch, hold and devour animal prey. Plants also harness animals in order to reproduce.

Many plants use complex trickery or provide snacks and advertisements (colours) to lure in pollinators, communicating either through direct deception or rewards. Plants even distinguish between different pollinators and only germinate their pollen for the best. Conversely, plants have a wide variety of toxic compounds to ward off predators. Notably, plants determine and apply the smallest quantity of resources that will solve the problem by releasing the toxic compounds only in the leaf that is under attack. As was argued by Charles Darwin, recent research indicates that the key to plant intelligence is in the radicle or root apex. Individual root apexes are not particularly capable. However, most plants have millions of individual roots, each with a single radicle. So, the destruction of one leaf or one root does not lead to the demise of the plant.

While humans have five basic senses, plants have at least 20 different senses used to monitor complex conditions in their environment. In addition that correspond approximately to the five human senses, plants have additional ones that can do such things as measure humidity, detect gravity and sense electromagnetic fields.

At the same time, plants are complex communicators, for example, through the use of chemical volatiles, electrical signals, and vibrations. In these ways, plants share information with neighbouring plants, insects, and/or other animals. For example, the scents of flowers when in bloom and when rotting are different messages for pollinators. Plants can even warn others of their species when danger is near. If attacked by an insect, a plant will send a chemical warning signal to their fellows. Furthermore, plants differentiate in their communications. This happens when they react differently to plants from the same parent as those from a different parent (Baluška, Volkmann & Mancuso, 2006; Farmer & Ryan, 1990; Hance, 2015; Hutchings & Dekroon, 1994; Mancuso & Viola, 2015; Trewavas, 2009).

2.1.7 Microbial

Microbial intelligence is shown by microorganisms. Microbes exhibit similar characteristics of intelligence as humans, such as self-awareness, association and adaptation, decision making, robust adaptation, and problem solving capabilities. This includes complex adaptive behaviour shown by single cells; and altruistic or cooperative behavior in populations of like or unlike cells. Microbial intelligence involves, for example, chemical signalling that induces physiological or behavioral changes in cells and influences colony structures.

Bacteria, which show primitive behavior as isolated cells, can display more sophisticated behavior as a population. These behaviors occur in single species populations, or mixed species populations. It has been suggested that a bacterial colony loosely mimics a biological neural network. The bacteria can take inputs in form of chemical signals, process them and then produce output chemicals to signal other bacteria in the colony.

The mechanisms that enable single celled organisms to coordinate in populations presumably carried over in those lines that evolved multicellularity, and were co-opted as mechanisms to coordinate multicellular organisms. Bacteria communication and self-organization in the context of network theory has been investigated. This has led to development of a fractal model of bacterial colony and identified linguistic and social patterns in colony lifecycle (Ford, 2004; Nui & Wang, 2012; Westerhoff et al. 2014).

2.2 Artificial intelligence

Fundamental studies across species relate intelligence to emergent behaviours related to self-awareness, robust adaptation, association and anticipation, decision-making, and problem solving (Westerhoff, 2014). Accordingly, these are the categories used here in consideration of artificial intelligence.

2.2.1 Self-awareness

The notion of self-aware AI is well established. For example, visitors to the 1939 New York World's Fair were able to enter the miraculous World of Tomorrow. This was an artificial world where visitors could meet Elektro the robot, and his pet robot dog Sparko (Jackson, 2011). Still in 2016, AI that has self-awareness and is at least equal to the general intelligence of human beings (Turing, 1950), which is referred to a Strong AI, is hypothetical. Strong AI is a topic of debate. It can be perceived as a miracle liberating human beings from the drudgery of mundane activities or a monster that will put an end to humanity or at least bring chronic mass unemployment.

For those who develop AI, exceeding human intelligence is a persistent mission involving efforts to mimic human mind, behaviour and actions. On the other hand, the implementation and influence of Strong AI may be moderated by many practical considerations. By contrast, Weak AI is not intended to mimic human beings, and there is no intention that AI should be able to feel, perceive, or experience subjectively. Rather, weak AI is focused upon the economic, reliable, fast execution of tasks within one narrow activity. This is the AI that can be found in an increasing number of devices and apps (Fox, 2017). It has been proposed that it is useful to define six levels of AI from 0 to 5 (SAE, 2016), of which Level 5 could involve something close to AI self-awareness. These levels can be summarized in relation to driverless cars.

At Level 0 (No Automation), there is no AI so the human driver (human) controls the vehicle through controlling steering, throttle, brakes, etc. At Level 1 (Driver Assistance), most functions are controlled by the driver, but still controlled by the driver but a specific function, such as steering under certain road conditions, can be done automatically by the car. At Level 2 (Partial Automation), at least one driver assistance system of "both steering and acceleration/ deceleration using information about the driving environment" is automated. This could be cruise control and lane-centering. It means that the human driver is disengaged from physically operating the vehicle by having his or her hands off the steering wheel AND foot off pedal at the same time. However, the human driver must still always be ready to take control of the vehicle. At Level 3 (Conditional Automation), human drivers are still necessary, but are able to completely shift "safety-critical functions" to the vehicle, under certain traffic or environmental conditions. It means that the human driver is still present and will intervene if necessary, but is not required to monitor the situation in the same way it does for the previous levels. At Level 4 (High Automation), vehicles are fully autonomous. Level 4 vehicles are "designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. However, this full automation is limited to the "operational design domain (ODD)" of the vehicle—meaning it does not cover every driving scenario. At Level 5 (Full Automation), a fully autonomous system should be at least equal to that of a human driver, in every driving scenario—including extreme environments like dirt roads, which are unlikely to be navigated by driverless vehicles before 2020 (SAE, 2016).

2.2.2 Robust adaptation

An important feature of intelligence is robust adaptation to changes in status and environment. This can require self-awareness beyond the capabilities of AI in 2016. However, there is some research, development, and innovation work aiming to improve the adaptation potential of AI. Such work encompasses, for example, neural networks, individual robots, and robot swarms (Wang et al., 2016). For example, having robots learn appropriate behaviours in response to damage with trial-and-error algorithm. This allows robots to adapt to damage in less than two minutes without requiring self-diagnosis or pre-specified contingency plans. Experiments revealed successful adaptations for a legged robot injured in five different ways, including damaged, broken, and missing legs, and for a robotic arm with joints broken in 14 different ways (Cully et al., 2015).

Also, there is research into the potential for adaptation among swarms of robots, such as adaptive collective foraging. This involves a swarm of robots searching and retrieving food-items. Robots have to switch between foraging and resting in order to maximise the net energy income to the swarm. The challenge is to achieve this with no centralised control and robots with only minimal local sensing and communication ability. Individual robots have interaction rules inspired from the widely observed self-organisation phenomenon in biological system, so as improve the energy efficiency at the group level.

There are three cues: internal cues, social cues and environmental cues. The combination of these cues could result in two interesting phenomena at the group level: positive feedback and negative feedback, which are believed to be important components in the emergence of self-organised behaviour in social insects or animals colonies. Experiment results show that the robot swarm with these strategies seems to be able to guide itself towards energy optimisation collectively (Liu and Winfield, 2010).

2.2.3 Association and anticipation

Associative learning involves linking together pieces of knowledge which, in turn, can enable anticipation of what will follow. Within AI, knowledge can be structured in ontologies, which encompass the constructs within a domain and the inter-relationships between them. Among the things that AI needs to have knowledge of are properties, categories, and relations between objects; events, states, and time in situations; as well as relationships between causes and effects.

Whereas natural intelligence can proceed on the basis of working assumptions based on recollections of past experiences, AI needs precise definitions of exact objects, situations, etc., to work with. This involves trying to establish objective definitions for things that involve dynamic complexity, such as a position in a situation being a vulnerable position. This involves computational semantics: in other words, the computation of meaning. As exactly the same thing have very different meanings in different settings, the computation of meaning is a profound challenge. Hence, establishing AI knowledge bases can be a massive undertaking until AI can understand enough concepts to be able to learn by reading from sources like the Internet, and thus be able to add to its own ontology.

There are many different types of learning in AI including: artificial neural network learning; association rule learning; Bayesian network; cluster analysis; decision tree learning; deep learning; inductive logic programming; reinforcement learning; similarity learning; and support vector machines. In particular, association rule learning involves discovering interesting relations between variables in large databases, such as certain types of purchases being related to each other and indicating a change in the status of a shopper: e.g. from single to married etc. Association rule learning can include: multi-relation association rules and context based association rules (Reza et al., 2014; Shaheen et al., 2013).

2.2.4 Decision-making

The fundamental decision for AI is what to do next: i.e. action selection. There can be different levels of abstraction for specifying an act ranging from micro to macro. For any one action-selection mechanism, the set of possible actions is predefined and fixed. The difficulty of decision-making increases as the number of potential tasks, need for speed, and complexity of environments increases. The mechanism for action selection can be highly distributed, as it is with distributed natural organisms such as social insects, or it may be centralised. The action selection mechanism affects the AI's impact, directs its perceptual attention, and updates its memory.

When there is machine learning, actions can lead to modifications of AI capabilities. Artificial action selection mechanisms can be divided into several categories including: symbol-based systems, distributed solutions, and dynamic planning. Symbol-based systems are based on foundational thinking about AI, and have been found to bring slow action speeds. Distributed systems can be inspired by neural networks research, and involve many modules running in parallel to determine the best action. However, distributed systems can also have executive decision systems to determine which module deserves the most attention.

Dynamic planning can involve computing individual next actions every instant based on plans and contexts. This can limit combinatorial explosion but limit flexibility if there is too much reliance on pre-coded plans. Accordingly, hybrid techniques can sometimes be used. These can involve automated updating of plans when better plans are found through search. Some dynamic planning models have been inspired by ethology research into instinctive behaviours, which can be considered to be fixed action patterns that are common among a species and usually runs from start to finish with little variation (Girard et al., 2002; Negatu and Franklin, 2002).

2.2.5 Problem solving

Problems can be considered to be single state, multi state, contingency, or exploratory. Problem solving can involve self-awareness, robust adaptation, association, anticipation, and decision-making. The settings of problems can be important to solution implementation. For example, an embodiment of AI for painting cars has different constraints to an AI application for use in carrying out surgical operations in a hospital. Crucially, problem solving can involve collective intelligence. Here, the development of AI has been inspired by swarm intelligence in nature. For example, swarm intelligence is the collective behavior of decentralized, self-organized systems. Examples include insect colonies and swarms. For example, honeybee swarms have been shown to process information in a remarkably similar way to the primate brain. The swarm utilizes massively parallel information processing and has a spatially distributed memory, mechanisms for focusing attention, an ability to discriminate and to filter out distractors and also to avoid functional fixedness.

It has also been found that a swarm can achieve a near optimal trade-off between decision accuracy and decision speed (Foss, 2016). An analogous AI development is, for example, particle swarm optimization. This works on problems by iteratively trying to improve a candidate solution with regard to a given measure of quality. It solves a problem by having a population of candidate solutions (i.e. particles) and moving them around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position, but is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This can move the swarm toward the best solutions.

Particle swarm optimisation is a metaheuristic, as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics such as particular swarm optimisation do not guarantee an optimal solution is ever found (Zhan et al., 2009).

3. Multi-intelligent hybrid systems and hybrid beings

3.1 Multi-intelligent hybrid systems examples

Here, systems refers to purposeful structures formulated to comprise interrelated and interdependent elements including different types of intelligence. These different types of intelligence operate together in order to achieve the goal of the system. Such systems have well defined boundaries including scope of operation. M.I. systems are hybrid when they combine intelligences from different natural and/or artificial origins.

3.1.1 Natural intelligence + natural intelligence

Human beings have been combining their own intelligence with that of other living things for thousands of years. For example, plants and insects have been used to heal human cuts and wounds for millennia. Some such ancient practices are now supported by results from scientific research (Tian et al, 2013).

Also widespread has been the use of other animals' intelligences by human beings during farming and hunting. For example, cormorant fishing involved fishermen using cormorants to catch fish for people to eat. Cormorants had a ring fitted around their necks that prevented them from eating every fish that they caught. Instead, the neck ring was loosened after they had caught seven fish, so that they could eat the eighth fish as a reward. It has been reported that once their quota of seven fish was filled, the cormorants would catch no more until their neck ring was loosened (Hoh, 1988). Increasing human knowledge of the capabilities of different animals has led to consideration of new ways of putting animals to work for human beings (Burke, 1993).

3.1.2 Natural intelligence + AI

More recently, different types of AI have been added to different combinations of natural intelligences. For example, different types of AI now widely used during farming and hunting in so called precision agriculture. Interestingly, human beings can deploy the natural intelligence of other animals against AI. For example, Dutch police have joined forces with Guard From Above, a security firm based in the Hague, to keep wayward drones from causing trouble by snatching them out of the sky. Birds deployed by this security company can hit drones in such a way that they do not get injured by the drone rotors. First, the birds disable the drone that they are hunting, then they retrieve and bring it to the human being wanting the drone to be put out of action (Thielman, 2016).

More generally, the combination of human intelligence with AI apps is increasingly widespread as people use Web platforms and smart phones for during work, rest, and play. This follows on from so called, Intelligence Amplification (IA), involving human use of information and communication technologies to improve performance (Skagestad, 1993). Thus far, the efficacy of combining human intelligence and artificial intelligence has been variable (Hill, 2016), and hype about new apps is often soon followed by them being abandoned (Arthur, 2014).

Another combination of human intelligence and AI is so called human-based computation. This can involve the deployment of AI in co-ordinating, integrating, and/or interpreting the inputs of people in solving a problem (Rosenberg et al., 2016).

3.1.3 AI + AI

In 2016, there are relatively few AI only systems, which operate without any human intervention. One possible example is adaptronics. This involves combining smart materials and smart structures with intelligent systems. This is done to address rising demands for modern structural systems that go beyond the technical and economic limits of mechatronic systems. In practice this involves combining conventional structures, such as those for vehicles, with active material systems that extend classical load-bearing and form-defining structure performance by adding sensor and actuator functioning. These adaptive structure systems can adapt to their operational environments optimally in terms of, for example, low-vibration, low-noise function, dimensional stability. This, in turn, can lead to the protection of raw materials, the reduction of environmental stress (resulting from noise and emissions), to a decrease of system and operating costs and a higher functionality and efficiency of systems. Thus, although a human being may still be needed to drive a vehicle, the structure of the vehicle can be adapting automatically to whatever conditions it encounters (Bein et al, 2011).

3.2 Multi-intelligent hybrid beings examples

Combining different types of intelligences into hybrid beings involves the creation of sentient entities. Compared to hybrid systems, this can involve more ethical issues and engineering challenges. These include the issues and challenges involved in gene engineering, body hacking, and developing androids. M.I. beings are hybrid when they combine intelligences from different natural and/or artificial origins. Hence, common across different types of multi-intelligence hybrid beings can be adverse foreign-body reactions. These can range from foreign-body granuloma when human beings biologically reject an implant to foreign-body sociological reactions when androids are viewed by society as being threatening rather than helpful.

3.2.1 Natural intelligence + natural intelligence

While the combination of natural intelligences into systems has been common for millennia, the combination of natural intelligences into beings has been fundamentally limited to hybrids between different genera, different species within the same genus, and different subspecies within a species. These can occur naturally in stable environments, naturally in changing environments, and through direct human intervention (Arnold, 1996). Direct human intervention can now take place through, for example, gene engineering. This can include improving the properties of plants for human purposes by adding the genes of animals to them (Osusky et al, 2005).

3.2.2 Natural intelligence + AI

While the combination of natural intelligences with artificial intelligences into systems is increasingly widespread, their combination into beings is less common. If AI is added to natural intelligence, the resultant beings could be described as cyborgs (Halacy, 1965; Wejbrandt, 2014). If natural intelligence is added to AI, the resultant beings could be described as biorobots. Cyborgs are becoming closer to reality through so called, body hacking. This involves fitting intelligent devices within the human body. For example, a device analogous to a heart pacemaker can be fitted into the human body to bring about deep-brain stimulation. The device can then regulate the brain's electrical impulses and chemical levels via electrodes.

Applications of deep-brain stimulation may someday be more enhancing than therapeutic. For example, in 2013, a team from UCLA showed that the procedure could buttress memory, improve the ability to process, and store information. Then, in 2015, a study using rats determined that it could potentially stave off memory loss and dementia-like symptoms. In other words, in addition to making human beings smarter, deep-brain stimulation could also ensure that human beings remain smart for longer (Konnikova, 2015).

3.2.3 AI + AI

Embodied AI such as physical robots (i.e. not virtual software agents known as bots) are an example of many different types of AI being brought together in efforts to have multi-purpose AI beings. Physical robots can have some or all of the following characteristics: operate autonomously to some extent; ability to move around; able to accept electronic programming; process data including physical perceptions electronically; operate physical parts and/or physical processes; sense and manipulate environment; and exhibit behavior which mimics humans or other animals. These characteristics involve combining different types of AI including: automated reasoning, computer vision, machine learning, and natural language processing.

The use of physical robots is already widespread in many different types of settings including battle grounds, factories, greenhouses, homes, mines, and warehouses (e.g. Moubarak and Ben-Tzvi, 2012). If physical robots are developed to look as close to human beings as is possible, they may be described as androids (Ishiguro, 2007). Embodied AI also includes animats (Wilson, 1991).

4. Multi-intelligence principles

4.1 Apply post-anthropocentric objectivity

Anthropocentric perspectives continue even though their limitations are increasingly widely recognized for research and development concerning intelligence. For example, there are widely held anthropocentric views about the intelligence of domestic dogs (Coren, 2009). These include human perspectives of their intelligence being instinctive (what dogs are bred by human beings to do for them, such as herding); working and obedience intelligence (what dogs learn from human beings telling them what to do); and adaptive (what dogs can learn for themselves). Using tests originally designed to demonstrate the development of language and arithmetic in human children, research findings indicate that domestic dogs are as intelligent as "the average two-year-old child" (Gray, 2009). Such anthropocentric research ignores that dogs have intelligence attributes, which humans can never develop at any age. These include dogs being able to solve problem based on their superior olfactory abilities. For example, through their sense of smell domestic dogs can detect illnesses in humans including various forms of cancer (Horvath, 2008).

This example illustrates that if human beings are given test designed to demonstrate the development intelligence among dogs, human beings could be found to have very low intelligence (Chittka et al., 2012). Hence, when research is designed to encompass a wider range of intelligence attributes, such as self-recognition and means-end awareness, results support opinions that domestic dogs can be smarter than human beings (Howell et al, 2013).

An important outcome from post-anthropocentric research is that it can provide insights into the formulation of a more robust conceptual framework for general intelligence, which can be applied to many species including human beings (Hambrick, 2016). Through anthropocentric human eyes and through a microscope, many microbes, plants, fish, insects, birds, and animals can appear so alien, i.e. so fundamentally not human, that it may be difficult to attribute levels of intelligence anything close to human intelligence (Greenwood, 2014). This, however, is due to human cognitive biases such as observation bias and confirmation bias Rather, than lack of intelligence across nature (Freedman, 2010; Oswald & Grosjean, 2004).

Accordingly, it is important to seek to counteract anthropocentric biases with methods with proven efficacy for counteracting the effects of preconceptions (Fox, 2016b) when a multi-intelligent hybrid system or being is to be developed. This is necessary to enable the widest possible consideration of all types of intelligence, and so avoid excluding the best options for a multi-intelligent hybrid system. During the detailed design phase, anthropocentric factors may be considered during the design and development of user interfaces for human beings.

4.2 Aim for transformational effects

Multi-intelligent hybrid systems and beings can enable automational, informational and transformational effects. Automational effects and informational effects include new types of productivity based on the substitution of human labour, and the availability of more information for decision making. Transformational effects include new-to-the-world solutions being created that transform what can done (Mooney et al., 1996; Ross and Beath, 2002; Venkatraman, 1994).

Often, there is limited focus on transformational effects due to phenomena such as competence traps, success traps, path dependencies, and lock-ins. These can all involve human beings preferring to make incremental improvements within existing paradigms. Rather than transforming what can be done. This, in turn, can lead to the extinction of natural lifeforms and/or human organisations in the face of competition that is transformational (Sydow et al., 2009; Teger, 1980). Thus far, human beings often have been developing and applying AI to bring about automational and informational effects. For example, the company Ravn has developed AI to sift, index and summarise documents as a human crime investigator would do.

However, the AI can work much more quickly and without breaks. This relentlessness enables hundreds of thousands of documents to be processes every day. At the same time, the AI can learn and bolster its own knowledge base to become more efficient and effective in sorting through and classifying documents in terms such as “privileged” and “non-privileged” (Murgia, 2017). Beyond such automational effects, informational effects can be brought about by, for example, using AI to generate from data about one event a variety of written articles in the different styles of different publications (Anderson, 2012) or generate a variety of original artworks from the different styles of human artists (Rutkin, 2014). By contrast, transformational effects await development. For example, human beings have deployed AI to make street lighting more efficient through automating the adjustment of street lighting in response to the automated detection of movement (Leccese, 2013).

A transformational alternative would be adapt human vision through multi-intelligence inclusions that enable people to see clearly in any lighting conditions – day or night. An illustrated summary of relations between automational, informational, and transformational effects is shown in Figure 1 below (Fox, 2013). This indicates that transformational effects can be served by automational, informational and transformational effects. For example, transformational improvements to natural vision, which would be sufficient to eliminate the need for street lighting, could involve automational data processing and informational presentations.

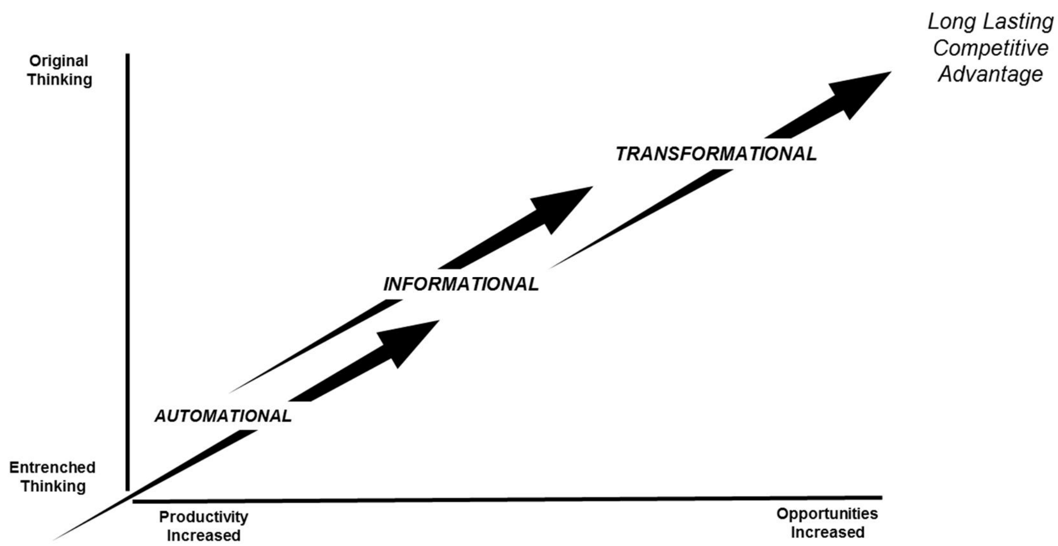

Figure 1. Automational, informational and transformational effects

4.3 Balance natural and artificial intelligences

Natural intelligences and artificial intelligences can have different strengths and weaknesses, which should be balanced to enable best outcome with resources available. In some cases, individual human beings can take the lead and determine outcomes with the aid of AI. Consider, for example, the online community of 3D printing enthusiasts: YouMagine.com. What they imagine is realised through AI applications that enable rapid engineering of their 3D digital sketches into 3D printed practical goods. By contrast, the AI application DeepDream takes initial digital images provided by people into unpredictable artistic directions. DeepDream applies a neural network to find and enhance patterns in images in order to create dreamlike art (Culpan, 2015). Similarly, Jukedeck takes initial human inputs for style, rhythm and intensity in unpredictable musical directions (Fildes, 2016).

While YouMagine, DeepDream, and Jukedeck apply AI to what individuals imagine, other AI applications can act upon the imaginative contributions of crowds. For example, crowd composition of original music and videos can involve different divisions of work between human imagination and AI engineering (Muñoz et al., 2016; Rutkin, 2015; Wilk et al., 2015).

Figure 2 below provides an illustrative summary of alternative balances between natural intelligence and artificial intelligence related to the extent of task scope. This illustrates that tasks with wide scope may be achieved best by natural intelligence carrying out most of the work. Notably, the oldest natural capabilities, such as psychomotor skills, are more difficult to reverse engineer into AI than newer capabilities, such as advanced mathematical reasoning (Goldberg, 2015; Moravec, 1988). Hence, it can be more technically feasible, economically viable, environmentally sustainable, and operationally practical to train birds to hunt down wayward drones than trying to develop an AI to hunt down wayward drones. At the same time, AI can be invaluable in, for example, automated mapping of drone paths and hunt bird locations (Thielman, 2016).

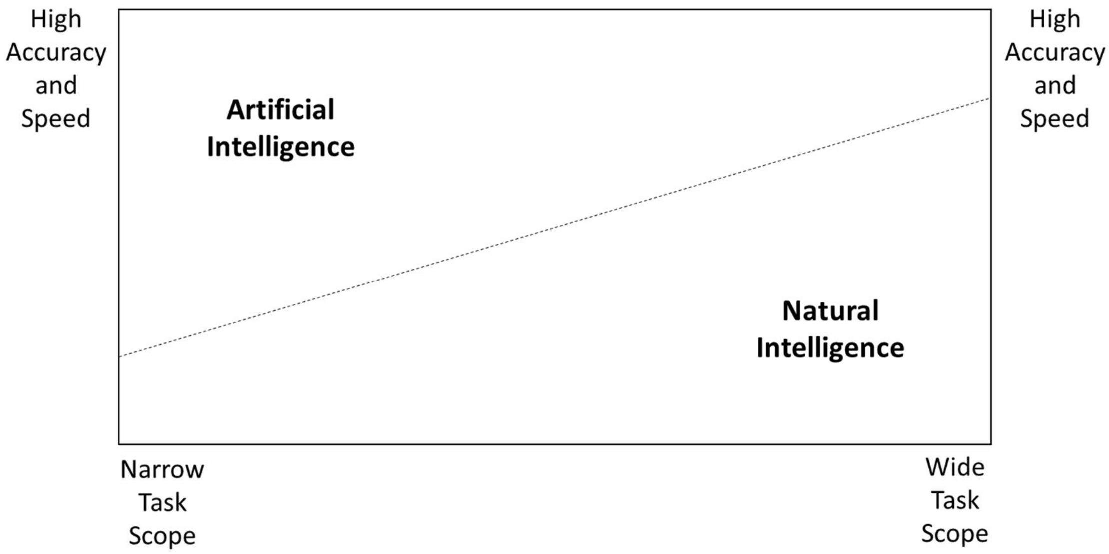

Figure 2. Different balances of natural and artificial intelligence across tasks with different scopes

4.4 Eliminate obsolete boundaries

Many boundaries, such as those between work and leisure, are rendered obsolete by multi-intelligence. For example, AI can act as on-demand film engineers, sound engineers, manufacturing engineers as human beings express themselves in their leisure time through self-broadcasting, music self-publishing, and personal manufacturing. This AI enabled engineering is easily, quickly, and inexpensively accessed through, for example, online communities and smart phone apps. AI apps do not have a limited number of fixed working hours that have to be agreed in advance, and may change at short notice. Rather, AI apps work on demand whenever they are needed for as long as they are needed.

Self-expression during leisure time can lead to financial remunerations ranging from small infrequent amounts to huge income streams of many millions. This is because combing human imagination and automated engineering enabled by AI changes the well-established proposition that success is based on an original idea comes from one percent inspiration in an instant and 99 percent perspiration over subsequent months and years. Instead, automated engineering by AI apps can greatly reduce the amount and duration of human perspiration from initial idea to independent enterprise. In particular, independent enterprises that can serve long-tail demand of small numbers of niche sales in many different geographical regions. Thus, the socio-economic mode of work by one person can change rapidly as an initial idea is prototyped, market tested, introduced internationally, and an independent enterprise is set-up. This can lead to rapid transition from informal unpaid consumption work to formal paid commercial work.

At the same time, new goods and services introduced in this way may be open, both technologically and legally, for original adaptations by those who acquire them. This, in turn, introduces autocatalytic economic possibilities. In particular, informal unpaid self-expression can lead to new enterprises offering goods / services, which then involve others in informal unpaid self-expression that can lead to further new enterprises (Norris, 2015; Ross, 2014).

The rapid cheap automated engineering introduced by AI apps is essential to these new autocatalytic economic possibilities. This is because people no longer have to be, or have to hire, human engineers during creating the goods and services that they imagine. This enables rapid low cost prototyping, market testing, and international introduction of new goods and services (Fox, 2017).

More generally, multi-intelligence affects boundaries between consumption and production throughout many sectors as people are able to carry out many more tasks themselves where they are, which they would previously have had to wait for others to do for them at much higher costs (Acampora et al, 2013; Rabbitt et al, 2015). More profound boundaries, which may become obsolete, are those between natural intelligence and artificial intelligence as these are combined in cyborgs and androids. However, the full potential of M.I. is not likely to be realised if anthropocentric preconceptions are not replaced by post-anthropocentric open-mindedness.

5. Directions for research, development, and innovation

Metaphysics, socio-technical theory, semiotics, and systems engineering are relevant to research, development and innovation concerning the combination of different intelligences into hybrid systems and hybrid beings.

5.1 Reframing metaphysics

M.I. raises new philosophical questions about the nature of existence and identity. A major contribution of metaphysics is ontological description of categories of being and how they relate to one another. Categorisation of being involve consideration of identity and how identities change through different causes. The potential for, and bringing into existence of, multi-intelligence hybrid beings expands ontology beyond what have hitherto been separate evolutions of natural and artificial intelligence. Metaphysical definitions for being and identity have profound implications for moral philosophy and political philosophy. Moral philosophy encompasses meta-ethics, normative ethics, and applied ethics. Meta-ethics seeks to determine the meaning and truth of moral propositions. Normative ethics seeks to determine what should generally be believed to be right and wrong. Applied ethics seeks to identify the morally correct course of action in various fields of everyday life at various levels, including: national, clinical, professional, organisational, and individual decisions (Beauchamp, 2001).

Following from Asimov's Three Laws of Robotics, the development of AI has encompassed ethics for decades including machine ethics and robotic ethics / roboethics (Tzafestas, 2016). Political philosophy is concerned with determining the meaning of liberty, justice, and rights, and their alternative means of realisation through government and law. Philosophical questions about the nature of existence brought about or changed by M.I., carry into ethical issues and how they should be addressed by government and through laws (Kymlicka, 2002).

These questions can be perceived and addressed differently through different philosophies of science, including: positivism, interpretivism, constructivism, and critical realism. These each have their own perspectives from the nature reality to the role of government in bringing about ethical behaviours. Within positivism, reality is measurable and desired effects can be brought about by government control of causal mechanism. Within interpretivism, reality is in the eye of the beholder, and government can seek to increase the probability of desired effects through aligning with those who have most influence in society. Within constructivism, reality is socially constructed through intersubjective convergence, and government can seek to bring about desired effects through extensive participatory debate, experimental interventions, and open-ended learning. Within critical realism, reality has three layers: why things happen, how things happen, and what people experience. In this critical realist view, government is part of a dynamic system which can only be steered with the active involvement of those who are governed (McAnulla, 2006).

Rather than seeking to assert the superiority of one philosophy of science over others, future work should encompass different philosophies of science when addressing metaphysical questions from existence and identity through to ethics and governance. These can form the basis for later syntheses during sociological investigations.

5.2 Extending socio-technical theory

There are extant scientific theories that can initially inform the introduction of multi-intelligence hybrid systems and beings. These predictive theories include: technology determinism, social shaping of technology, technology domestication, and monster theory. Within technology determinism, technologies as seen as causal agents that transform society without people having much control over that transformation. Technology determinism has been summed up the phrase, “technology determines history” (Bimber, 1990). A response to technology determinism is the social shaping, or construction, of technology, which views human beings as having agency. In particular, human beings are viewed as being the shapers of technologies through different types of engineers who develop technologies and are influenced by their social contexts (Williams and Edge, 1996).

Technology domestication addresses how technologies are tamed through integration into everyday lives. Metaphorically, technology domestication focuses on the progression of technological devices from being perceived as being dangerous to being accepted as harmless in everyday life. Technology domestication studies have revealed that the integration of technologies into everyday lives is not the same as them being viewed positively (Silverstone and Hirsch, 1992).

Monster theory draws upon anthropological studies to explain public moral perceptions about technological innovations. In particular, perceptions of technologies are viewed as being mediated by cultural beliefs and contemporary myths about what is natural and what it means to be human (Smits, 2002). Monster theory can easily be related to the ‘uncanny valley’, which is a term for the discomfort human beings feel when something mimics nature too well for human psychological comfort (Mori, 2012).

AI being able to learn and self-replicate undermines the fundamental premises of technology social shaping and technology domestication. At the same time, AI being able to learn and self-replicate introduces new support for technology determinism and new directions for monster theory. Hence, the introduction multi-intelligence hybrid systems and hybrid beings calls into question the bases of extent socio-technical theories; and calls for the formulation of new theoretical constructs that can enable better prediction of social responses and social outcomes.

Furthermore, the new theoretical constructs should have a post-anthropocentric perspective that encompasses other societies in nature as well as human societies. Moreover, the introduction of multi-intelligence hybrid systems and hybrid beings brings fundamental questions about what makes up a society when its populations are hybrids. Hence, social biology and social psychology need to be taken into consideration when extending socio-technical theory (Bainbridge et al., 1994; Wilson and Wilson, 2007).

5.3 Integrating semiotics

The making of meaning is studied in semiotics. Semiotics is distinct from linguistics as it encompasses non-linguistic sign systems. Semiotics encompass semantics, syntactics, and pragmatics. Semantics addresses the representation of meaning in different forms of communication including audible and silent expression. Syntactics considers structures in the communication of meaning. Pragmatics considers the ways in which context contributes to meaning (Danesi, 2007). Meaning making runs through metaphysical consideration of existence into the socio-technical consideration of the meaning of specific innovations in specific situations.

From an anthropocentric perspective, semiotics includes viewing all human cultural phenomena as forms as communication. Semiotics also encompasses biosemiotics and computational semiotics. Biosemiotics seeks to integrate semiotics with findings from biology. Biosemiotics has two basic foci: vegetative semiotics studying semiosis at the cellular and molecular level including sign-mediated interactions in bacteria communities such as quorum sensing and quorum quenching; and zoosemiotics semiotics studying organisms with neuromuscular systems (Kull, 1999). Computational semiotics draws upon studies in logic, mathematics, cognition, and linguistics, as well as established semiotics. An important topic in computational semiotics is sign-theoretic perspective AI knowledge representation (Andersen, 1991).

The study of meaning making for multi-intelligence hybrid systems and beings requires integration of semiotics, biosemiotics, and computational semiotics. This integration involves semiotics that are planned in advance rather than only studied during their occurrence. This has already been the case to some extent in computational semantics. However, that has had an anthropocentric perspective as it has focused upon human-computer interaction (HCI).

Furthermore, planning in advance needs to consider how different types of meaning will be created at the metaphysical level by the development of different multi-intelligence hybrid systems and beings. It is to be expected that different human cultures can perceive the same systems and beings in different and opposing ways. This diversity of perceptions about the nature of existence and identity can be further increased as multi-intelligence hybrid systems and beings form their own opinions about others. Then, planning in advance needs to address how multi-intelligence hybrid systems and beings will formulate meanings for communication to others for maximum reliability and validity. Here, reliability involves the maximum number of communication recipients understanding a communication in the same way. Here, validity involves the maximum number of communication recipient understanding a communication in the same way as the sender intended.

5.4 Systems engineering for multi-intelligence

Systems engineering is concerned with design and application of the entire systems, rather than parts. System engineering looks at challenges in their entirety, while taking account of all the facets and all the variables and linking the social to the technological. This involves identification and quantification of system goals, creation of alternative system design concepts, selection and implementation of the best design, verification that the design is properly built and integrated, and post-implementation assessment of how well the system meets the goals.

Systems engineering is a well-established discipline with an international council (Gianni et al., 2014; Goode et al., 1957). Established systems engineering methods are relevant to the development of multi-intelligence hybrid systems and beings. However, more fundamental factors need to be taken within the scope of their systems engineering. These include: moral philosophy, political philosophy, social psychology, and semiotics. At the same time, systems engineering needs take inputs from the latest findings from scientific research into the nature of intelligence. For example, it has been argued that learning about general intelligence in non-human species is an essential component of developing a complete theory of general intelligence. This is feasible because testing cognitive abilities in other species does not depend on ecologically relevant tests. Then, discovering the place of general intelligence among traits in other species will constitute a major advance in understanding the evolution of intelligence (Ardena & Adams, 2016).

Also, new research study findings about how different types of beings affect each other need to be taken into account. These include studies of so called “social genetic effects”. Such studies investigate how the fundamental nature of others affects the well-being of those they interact with (Baud et al., 2017). As the systems engineering can bring about fundamentally novel natures in multi-intelligence hybrid systems and beings, the diversity of effects on others should be considered from new perspectives. This will require going beyond the usual types of external analyses carried out in systems engineering where there is much more prior knowledge of the likely reaction of others. In particular, fundamental consideration will need to be given to interactions between structure and agency; and the new ways in which multi-intelligence enables them to shape each other (Archer, 2003).

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