Implications of Future Technology Environments

Modifications to the nature of human performance and the necessary skills to operate in a future technology landscape

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SWINBURNE UNIVERSITY OF TECHNOLOGY

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Executive Summary

Aim

The aim of this collaborative research program between Swinburne University of Technology and the Defence Science and Technology Organisation is to identify the critical skills and necessary human performance requirements (both cognitive and physiological) for the future warfighter working as part of a complex human-machine environment.

Background

Human-machine boundaries are shifting, such that concepts of identity, autonomy, responsibility and trust need to be re-examined within a cognitive framework that can accommodate sensory and physical augmentation, complex information management and cognitive processes distributed across humans, machines and human-machine interfaces. This report focuses on measurement and modelling of human capabilities and performance, particularly in the cognitive domain.

Measures of mental workload and performance

We begin with an overview of the long history and wide range of measures of mental workload and performance. Many of these have been shown to have good reliability and predictive validity, such that many of them work well to measure and predict capability and performance within specified domains. There is less confidence in the criterion validity and construct validity of measures of mental workload and associated psychological variables, and only limited consensus on the relationship among physiological measures and their putative cognitive correlates. A major concern with measuring cognitive parameters is whether they actually reflect an underlying quantitative structure to be measured. While the information-processing models of human cognition that are commonly used in human factors research have provided useful frameworks for guiding the development of human-machine interfaces and for solving problems in specific task environments, they may not be sufficiently robust to support consideration of future human-machine environments and unknown task scenarios. Different philosophical approaches to cognition, such as the notion of embodied cognition, phenomenological approaches that emphasise sense-making through the nature of interactions with agents and environments, and approaches supporting the distributed nature of cognition, need to be explored.

Dominant models of human cognition

Applied cognitive psychologists and human factors specialists operate somewhere along the scientist/practitioner spectrum. Those who identify most strongly with the scientist end of the spectrum tend to develop cognitive models to generate testable hypotheses regarding theoretical constructs. However many scientists and practitioners consider that their models serve primarily to provide a framework for what needs to be explained and to generate useful methods for specific analyses or evaluations of task environments. Models as frameworks can facilitate communication within cross-disciplinary research teams but it is important to be aware of the discipline-specific assumptions within such models that may not be understood by those from other disciplines. We present the common multi-level information-processing models of individual human cognition underlying measures of human capability and performance. It has been clearly articulated in the literature that system-level models of interactions and transactions between agents within systems are needed, as are better theoretical modelling of perception-action coupling and multi-sensory integration. We reiterate this call and emphasise that more comprehensive and theoretically-sound models are particularly critical for the future human-machine environment, where sensory and physical augmentation and human-machine teamwork will challenge the individual, human perspective on cognition.

Experimental program

This Swinburne-DSTO research program includes experimental work being undertaken by a Masters student in applied psychology.

This experimental program explores the strategies used by individuals to process information in a dynamic task environment, and to resume that dynamic task after interruption of input, but while the task remains ongoing. In the first study, we interrupt the ongoing, dynamic task using visual occlusion, whereas in the second study, we investigate information gathering strategies from a second dynamic task. In the third study, we will investigate cognitive strategies and performance implications undertaking the second dynamic task while simultaneously engaged in the primary ongoing, dynamic task.

The first study of this program aims to identify potential cognitive, physiological, and performance correlates of visual attention during a visual-occlusion paradigm in an ecologically-valid dynamic task (a driving simulation game). We aim to identify the length of time that vision can be occluded without compromising performance along with the strategies for dealing with occlusion in both predictable and unpredictable occlusion scenarios. The degree to which different cognitive, physiological and observational data are predictive of performance will be evaluated. The second study aims to identify the amount of time required to acquire different forms of information from a small screen presented in different locations and the degree to which information can be acquired sequentially through multiple brief presentations versus one longer presentation. The effect of different types of cues for the location of the screen (central versus peripheral, valid versus invalid, visual versus auditory) will be evaluated, and we will also investigate whether the speed of information retrieval can be improved with training. The third study will evaluate performance in a dual task condition to investigate switch costs and task-switching strategies using these two dynamic tasks and the conditions under which the information retrieval task captures attention beyond a planned look-away time from the primary task.

Conclusions

1. Measures of human cognitive capability and performance require more conceptual clarity and greater construct validity to be useful in understanding future human-machine scenarios. Understanding and quantifying dynamic aspects of human teamwork (cognitive, affective, physical) may provide guidance for future human-machine interfaces.
2. A better conceptual framework for understanding the perception-action cycle is required for understanding how best to provide sensory and physical augmentation and to share information between humans and machines.
3. There is a need for a sound philosophical framework for understanding the evolving distributed nature of human cognition and performance as "virtual environments" and new technologies become an accepted component of the "real world" with which we interact.
4. A philosophical framework is also required for understanding the notion of trust, autonomy and accountability in the context in which machines are capable of acting as autonomous agents without direct human oversight. Within this context, it is important to explore the degree to which human capabilities and performance are limited by the constraints of the natural environment in which they evolved (pre-technology, pre-civilisation earth).

Overview and Context

Background

This collaborative research program between Swinburne University of Technology and the Defence Science and Technology Organisation seeks to understand the human performance requirements of future warfighters operating within the technological environment expected to be available into the year 2050. Future human performance requirements centre on the information management strategies, attentional mechanisms, and performance indicators (both cognitive and physiological) that underpin effective future human-machine interface technologies. As technology advances, the integration between humans and the technology they use is becoming increasingly seamless. It is anticipated that by 2050 partially autonomous systems that require human interaction from a remote location will be the norm. In this environment, it will become increasingly important to understand the necessary resource allocation, information management, and decision-making skills required to support the effective monitoring and control of multiple assets within these complex socio-technical systems. The design of technology interfaces and the allocation of tasks between human and machine must take into account the implicit and explicit information-processing strategies supporting skilled human performance and the human interaction with semi-autonomous and fully autonomous systems. This will be critical to determine the modifications to recruitment and training strategies necessary in order to meet human performance requirements in this new warfighter environment.

Aim

This collaborative research program aims to identify the critical skills and necessary human performance requirements (both cognitive and physiological) for working as part of a complex machine environment. The research program also has the potential to develop criteria for technology interfaces that will allow ADF personnel to work effectively within this environment while meeting concurrent social, ethical and political considerations with minimal performance cost.

Method

The method of study employed on this project has been:

1) To develop laboratory tasks suitable for testing implicit attention and skilled performance used in different human-machine interactions (for example, tasks simulating the monitoring and control of multiple UAV assets in complex environments);
2) To develop a methodology for determining physiological load in humans to predict human performance decrements;
3) To use these tasks to increase an understanding of the information-management and attentional skills required to achieve complex operations with:
    a) Single machines with differing levels of autonomy;
    b) Multiple machines with differing levels of autonomy;
    c) Multiple machines and multiple operators with differing levels of autonomy;
4) To monitor and review the future technology landscape to understand the types of technologies likely to be in operational use into the future;
5) To review the literature on information management strategies, skilled performance and autonomous systems to be able to provide on-going advice as to changes in the nature of skilled performance requirements to operate in a future technology landscape.

Organisation of this Report

The first section of the report will be in the form of a literature review of measurement of human capabilities and performance in the context of the dominant information-processing models of human cognition. It will then outline proposed future directions for cognitive models and frameworks that may be more applicable to the complex socio-technical environments of the near future.

The second section of the report will outline a series of laboratory tasks being undertaken that seek to understand the attentional strategies, information management and performance costs associated with predictable and unpredictable task switching in a dynamic task environment.

Measures of Mental Workload and Performance

Methodological considerations

Scientist-practitioner model

The human factors domain is focused on ensuring that the design of technology meets the needs of the users of that technology (Stanton et al., 2013). Like the discipline of psychology, the human factors discipline follow the scientist-practitioner model, in which the practice within the discipline is grounded in, and informed by, scientific research. Stanton et al. note that human factors specialists differ in the position they place themselves along the scientist-practitioner scale, depending on the type of work they undertake. Annett (2002a; 2002b) draws a distinction between human factors specialist as systems analyst, aiming to understand the nature of interactions between human and machine, and the human factors specialist adopting evaluative methods to test the design of specific human-machine interfaces. While analysts must be concerned with the construct validity of the methods they employ in their research, evaluative methods rely more on predictive validity and reliability.

For the most part, human factors specialists work on the design and evaluation phases of technology projects to ensure that human-machine interfaces meet the needs of the users. Stanton et al. (2013) catalogue and evaluate over 100 human factors methods that can be applied to different problem spaces, ranging from qualitative and observational methods (e.g., interviews, checklists, probes, video analysis) through to quantitative measures (e.g., reaction times, error, mental workload, physiological and biofeedback measures) and analytic methods (e.g., task analysis, flow charting, network analysis). Human factors specialists, especially those working in complex, high stakes task environments (aviation, medicine, military) need to be relatively pragmatic about the methods they adopt, given the likely constraints on access to the technology, the human operators, and the operational theatre. In the end, much of the human factors research undertaken in these domains is relatively agnostic with respect to the theory underlying the methods adopted. If the methods provide usable data and the frameworks and models from which they derive serve as effective inter-disciplinary communication tools, the work is deemed to be of high value.

However, the context of this report is consideration of the human-machine environment in future technology landscapes looking at least twenty years into the future. This landscape is free of the constraints of any current specific task environment. Norman and Verganti (2014) note that most human-centred design methods operate successfully in the context of incremental innovation (improving innovative technology once it has been adopted in a task environment) but not so well in the context of radical innovation, where the constraints on context of use are unknown. For radical innovation, predictions about the constraints of human capability and performance must be theoretically sound in a scientific sense, rather than the more pragmatic sense that can be applied in known situations. Applied psychology / human factors specialists bringing their discipline expertise to open-ended future-oriented predictions must operate firmly at the scientist end of the scientist-practitioner model. In making broad claims about human-machine interactions into the future, there is no real-life system to measure, and no specific work domain to design, so the only basis for considering the role of the human in the human-machine environment is to begin with a scientifically-defensible model of human capability and performance.

Human performance measures

There are many measures of human performance, both in the form of physical and cognitive aspects of performance (e.g, see Anastasi & Urbina, 1977; Stanton et al., 2013; Weinberg & Gould, 2015). These measures can be roughly characterised as measures of human capacities, reflecting the cognitive, physical and affective capacities of humans in general or of individual human operators, and measures of task performance, reflecting the actual performance of human operators on specified tasks or in specified situations. Types of performance measures may be in the form of speed of responding or errors in terms of relevant task parameters, or in terms of physiological or behavioural indicators of cognitive or physical factors. Measures of cognitive or physical workload are used to estimate the workloads imposed by specific tasks, and to measure the capacity of individual operators to meet these workload requirements. Workload measures can also be used to track the degradation of performance over time (e.g., due to vigilance decrements or fatigue).

One of the main advantages of machines over humans is the fact that a machine does not suffer from the perceived human frailties, like becoming bored or fatigued by repetitive tasks, or becoming emotional and erratic in performance under mentally or physically stressful conditions. In fact, machines tend to excel at tasks that tire or bore humans. But in stark contrast to this, machines often have great difficulty with tasks that humans find easy (Minsky, 1988), machines do not deal well with even low levels of uncertainty and complexity, and are difficult to endow with the notion of "common sense". Although it is beyond the scope of this report to discuss in detail, human moods, emotions, personality factors and adaptable arousal levels may prove to be an intrinsic component of the most positive aspects of human capability within future human-machine environments (Damasio, 2008; LeDoux, 1992; Minsky, 2007; Norman, 2005).

As the nature of the human-machine environment becomes more complex, it is imperative that we begin to understand the technical specifications of the humans in the human-machine system, just as we understand the technical specifications of the machine components. Although we have a range of potential measures of human "technical specifications" in the form of standard psychological and physiological parameters (personality measures, measures of aptitude, intelligence, emotional intelligence, physical performance measures used in sport), the construct validity of these measures often contested, particularly when employed outside of their original context of development and usage. For example, many psychological tests were originally developed in the context of clinical populations for differential diagnosis, but are now widely used in normal populations to measure individual differences on putative psychological factors defined by reference to performance on these instruments (Frances, 2013).

Reliability and validity

Psychological constructs such as cognitive capacity, attentional effort and mental workload are not directly observable, and can only be measured through inferential methods. The concepts of reliability and validity are thus fundamental to psychological measurement (Anastasi & Urbina, 1977). Reliability refers to the attribute of consistency in measurement and is best described as a continuum from inconsistent to completely reproducible under specified conditions. The different types of reliability include temporal stability (e.g., test-retest reliability), internal consistency (e.g., split-half, coefficient alpha), and inter-rater reliability, which confirms that tests administered by independent assessors produce similar results. In contrast, a measure is deemed valid to the extent that it measures what it was intended to measure, and to the extent that inferences made from the measure are appropriate, meaningful, and useful. Approaches for collecting evidence that demonstrate the validity of a measure can be classified into content, construct, and criterion validity. Content validity and construct validity measure the degree to which the content of the measure relates to the construct being measured, and the overall degree to which the construct makes sense conceptually. Criterion validity and predictive validity are related to future behaviour or performance. Face validity refers to the degree to which a measure is accepted by stakeholders as valid. Face validity is often linked to the surface similarities between the measure and the layperson's view of the construct being measured and is rarely considered in psychological testing. However, face validity can be surprisingly important in applied settings where practical outcomes are the main focus and people examining business cases must be convinced of the utility of each approach (Anastasi & Urbina, 1997).

With regards to the human machine environment, construct validity or evidence that a measure actually captures the underlying theoretically-derived conceptual construct it is intended to, and predictive validity, are especially important. Although the concepts of reliability and validity are widely used in the context of psychological measurement, there has typically been less emphasis on the psychometric properties of human factors methods. There is less focus in the human factors domain on the 'scientist' aspect of the scientist-practitioner model (developing hypotheses, using rigorous data collection and analysis techniques and disseminating research findings that test theoretical models), and more emphasis on the 'practitioner' end of the spectrum. The practitioner focuses on applying models and methods to real world problems, addressing the constraints inherent within these environments, and developing and evaluating cost-effective solutions to identified problems. In the human factors domain, theoretical models serve primarily as frameworks for analysis, evaluation and communication rather than the fundamental principles of their domain.

Psychological Measures

Psychological assessment is mostly directed toward personality traits and cognitive abilities. This section will focus on the measurement of cognitive abilities and performance rather than on personality measures, and these are generally measured using intelligence and aptitude tests. Intelligence tests produce an overall score based on results from a heterogeneous sample of items, whilst aptitude tests measure more clearly defined and relatively homogenous segments of ability. These tests are often used to provide an indication of cognitive functioning and to predict performance in other domains, including educational and workplace setting.

Intelligence tests

Currently, the most widely used intelligence test is the Wechsler Adult Intelligence Scale (WAIS; Wechsler, 2008) which comprises fifteen subtests that produce a global IQ score and four index scores relating to verbal comprehension (including verbal reasoning, verbal expression, acquired cultural knowledge), perceptual reasoning (including spatial reasoning, inductive reasoning, problem solving), working memory (including attention, mental control, concentration), and processing speed (including visual perception, visual motor coordination). The WAIS not only provides a measure of general intellectual functioning, but allows for the examination of intra-individual strengths and weaknesses across different index and subtest scores. However, the overall global IQ score may be misleading when there is significant variation in subtest scores that generate the index scores contributing to the global IQ score. The same global score may reflect substantially different patterns of subtest and index scores, and these patterns of scoring may provide a more meaningful and nuanced representation of overall cognitive ability. A major disadvantage of the WAIS is that it is time-consuming to administer, score, and interpret, and it must be administered by a registered psychologist. For this reason, despite its well-known psychometric properties (Lichtenberger & Kaufman, 2009), it is not often used as a measure of intelligence in applied settings.

An alternative to the WAIS is the Kaufman Brief Intelligence Test (KBIT; Kaufman & Kaufman, 2004), a brief intelligence screening test that provides an overall general intelligence score and two scale scores, a verbal score, also referred to as crystallised knowledge and a non-verbal score, also referred to as fluid intelligence. Verbal or crystallised intelligence is made up of items that assess verbal comprehension, reasoning and vocabulary knowledge, whereas non-verbal or fluid intelligence is made up of a matrices test that assesses the ability to identify relationships among meaningful and abstract visual stimuli. Both the WAIS and KBIT demonstrate good psychometric properties: reliability in terms of test-retest and internal consistency; construct validity as evidenced by significant correlations with related measures; and predictive validity in terms of predicting academic performance (Kaufman & Kaufman, 2004).

Despite evidence demonstrating the reliability and validity of these individual intelligence tests, the nature of the underlying construct of intelligence is still deeply contested (Neisser et al., 1996). As can be seen from the WAIS and the KBIT, each test generates a different overall intelligence score generated by different scale scores based on different subtests and items, suggesting two different conceptualisations of how general intelligence is constructed. Moreover, the evidence for the predictive validity of intelligence tests also needs to be re-examined in terms of whether the items on intelligence test (supposedly measuring an aptitude that will predict future performance) are actually different from those on the performance outcome measure.

Emotional Intelligence

More recently, there has been a shift in focus from general intelligence to emotional intelligence (e.g., Mayer et al., 1999; 2001; Pérez et al, 2005). Put simply, emotional intelligence can be described as the ability to perceive and interpret other people's emotions, as well as the ability to understand and regulate one's own emotional responses. Given the interest in emotional intelligence over the past two decades, there have been several notable attempts to operationalize emotional intelligence including the Mayer-Salovey-Caruso Emotional Intelligence Test V.2 (MSCEIT V.2; Mayer, Salovey, Caruso, & Sitarenios, 2003), the Emotional Competence Inventory (ECI; Boyatzis, Goleman, & Rhee, 2000), Schuttle et al.'s (1998) 33-item emotional intelligence scale and Bar-On's (1997) 133-item Emotional Intelligence Quotient Inventory (EQ-I; Bar-On, 1997). With the exception of the MSCEIT (Mayer et al., 2003), most emotional intelligence tests are typically self-report surveys that assume one is insightful enough to be able to report accurately and honestly about his or her own understanding and use of emotions, and his or her ability to perceive emotions in others. Although there is support for the reliability of emotional intelligence measures, there is limited evidence for the validity of such measures. In fact, similar to general intelligence and in the absence of a strong theoretical basis, emotional intelligence measures have produced different factor structures ranging from one to five-factor models, with scores on these measures being more strongly associated with personality trait variables than general ability measures (e.g., Bastian et al., 2005). This raises further questions about the construct validity of emotional intelligence and whether it is based on a defensible theoretical model. The predictive validity of emotional intelligence measures is limited and appears to explain less variance in performance outcomes compared to general ability measures, despite claims that it contributes more to overall performance. While it is indisputable that some form of "emotional intelligence" will be critical to human-machine interactions in future sociotechnical environments, current models of emotional intelligence require significant research and development.

Human Factors Methods

Human factors methods are used to address problems that impact negatively on the overall performance of a human machine system (see Vicente, 2004). Most of these problems are related to unexpected interactions at the human machine boundary. Stanton et al. (2013) describe 107 different humans factors methods that can be collapsed into task analysis methods, cognitive task analysis methods, process chart methods, human error identification and accident analysis methods, situational awareness methods, mental workload assessments, team assessment methods, interface analysis methods, design methods and performance time prediction methods. This report will focus on mental workload assessments as not only is it common practice to assess mental workload in the human machine environment, but rather this is particularly important for future warfighters who will be working in complex human machine systems.

Mental workload

Mental workload as a theoretical construct is concerned with measuring the cognitive resources available (individual perspective) or required (task perspective) to undertake a specific task in a specific context. While scientists aim to understand the nature of the cognitive resources in terms of their structural and functional components, practitioners take a more pragmatic view. For practitioners, mental workload is conceptualised as a multidimensional construct where stressors such as task demands, task difficulty, and constraints of the task environment as well as other environmental stressors negatively affect an operator, which in turn affects their performance (Megaw, 2005). It can be inferred through multiple methods including performance measures for primary and secondary tasks in dual task scenarios, psychophysiological recordings, and subjective ratings. Psychophysiological measures of mental workload involve objective physiological responses such as heart rate, heart rate variability, eye movements and brain activity that are assumed to be affected by, or indicative of, increased workload. These physiological recordings can often be collected during the primary task without having to interrupt performance whereas subjective rating involve participants reporting on the perceived mental workload associated with task performance either during or following the completion of the task.

The most widely used subjective measure of mental workload is the NASA Task Load Index (NASOA-TLXL Hart, 2006; Stanton et al., 2013). This scale is a multidimensional subjective rating tool based on a weighted average of six workload sub-scales, including mental demand, physical demand, temporal demand, effort, performance and frustration level. Since the operationalisation of mental workload in this measure comprises performance, physiological and subjective ratings, multiple methods of data collection are required. This multiple methods approach theoretically provides an advantage of triangulating data and supplementing objective measurement with subjective measures. However, Matthews et al. (2015) found that different sources of data did not always converge and that convergence should be empirically demonstrated prior to interpretations of any findings using this measure. While the sensitivity and internal consistency of these measures can be evaluated in specific task environments, their utility in predicting cognitive capacities and performance in future and more complex environments is contestable without a firmer understanding of the underlying constructs of interest and their relationship with the various sub-scales.

Methodological issues reprised

As noted earlier, both the construct validity and predictive validity of psychological tests of intelligence and emotional intelligence have been strongly contested, and suggests such tests are problematic in considering cognitive capabilities in future technology environments. There are also such concerns surrounding the measurement of mental workload in the human factors domain. According to Annett (2002a), subjective methods of measuring mental workload are fundamentally flawed for several reasons, including the level of disagreement between objective and subjective measures, sources of error such as poor inter-rater reliability and systematic effects such as timing, presentation order and contextual effects on subjective judgments. The reliance of subjective measures on introspection is limited by the amount and type of information available to conscious report. The amount of attention that can be directed toward the relevant stimulus can be comprised by the acts of introspecting and reporting. More importantly, sensory information that is not consciously attended to is therefore not available for conscious report even though it might be highly relevant to workload and performance. It should also be noted that the quality of subjective responses differs for novices versus experts such that experts are able to provide more in-depth and detailed subjective responses compared to novices. However it is not clear whether experts are reporting more detailed task knowledge (a conscious understanding of the task requirements at the point of introspection) or whether they are actually reporting on the cognitive activity they are engaging in.

More generally, however, a major concern relating to the use of tools to measure cognitive ability is the degree to which these measures violate the fundamental requirements for scientific measurement (Annett, 2002a; 2002b). That is, attributes such as intelligence and mental workload lack true quantitative structure that allow proper measurement. For example, we assign scores to intelligence, but there is no identifiable unit of measurement for the scores. At most, these scores are ordinal data. Although we can establish patterns in the data that have structure (i.e., factor analysis), this is not sufficient for establishing the theoretical validity of a construct that allows it to be confidently applied in a different context. It could be argued that within the psychology domain, intelligence can be viewed as a social construction, and it is what is being measured (the patterns of responses on tests of intelligence define the construct). Similarly, within the human factors domain, subjective ratings can be cross-validated with objective physiological and performance measures to provide confidence in the use of the measures in specific contexts.

We highlight the lack of theoretical models to inform the measurement of certain constructs, the underlying quantitative structure and true existence of these constructs, and the criteria for making sense of different sources of data so that interpretations are useful and meaningful. Given our focus on human capability and performance for the future warfighter operating within complex socio-technical scenarios, it is critical that the methods and measures offered by scientists to inform analysis be based on conceptually-sound and defensible theoretical models that can be scientifically validated.

We also note that there are many methods in human factors research for measuring putative cognitive resources required within complex task environments that we have not reviewed here. For example, there are many excellent resources outline methods for cognitive task analyses (e.g., Crandall et al., 2006; Hoffman & Militello, 2009; Stanton et al., 2013), cognitive work analysis (e.g., Naikar et al., 2006; Naikar, 2013; Rassmussen et al., 1994; Vicente, 1999) and frameworks for evaluating distributed situation awareness (e.g., Salmon et al., 2009). These approaches seek to understand workload demands from a task environment or system perspective with a view to understanding how to design better systems that manage workload more effectively. They are mostly designed to assist multidisciplinary teams undertake complex multidisciplinary analyses involving high level input from project sponsors, subject matter experts, technical designers, interface designers and system end-users, rather than to understand the basic underpinnings of human cognitive architecture.

Information Processing Model of Human Cognition

Multistore Model

Overview

The basic information processing model of cognition originally proposed by Atkinson and Shiffrin (1968) is illustrated in Figure 1. This model combines the processes of sensation and perception with a standard model of memory to describe how individuals gather, organise, interpret, process, and store information from the environment.

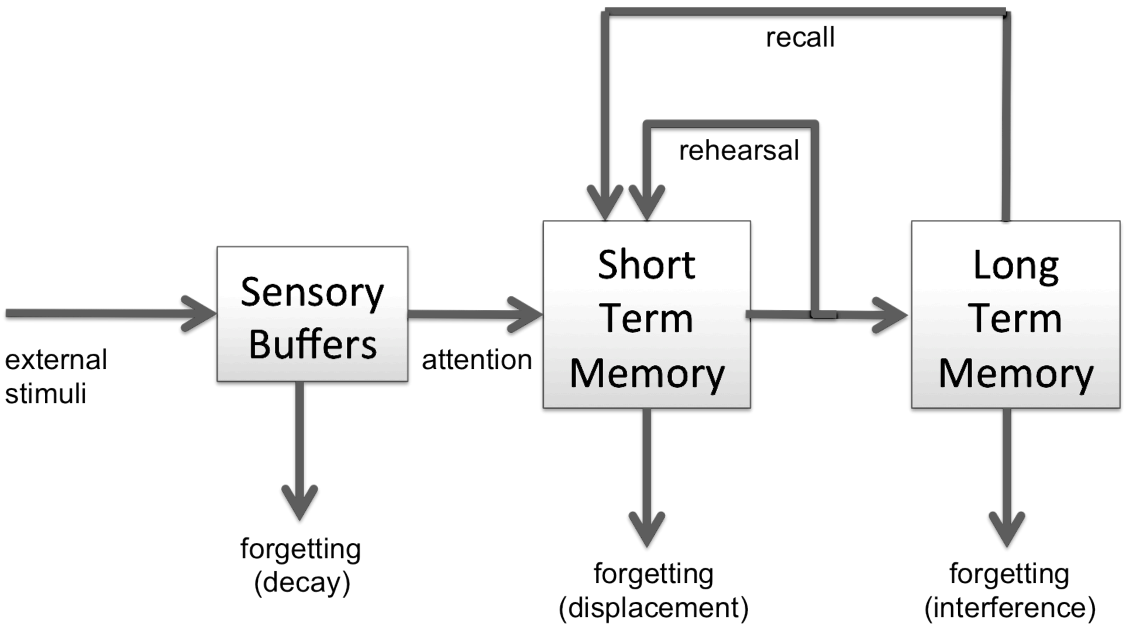

Figure 1. Multistore model of memory (adapted from Atkinson and Shiffrin, 1968)

Sensation

At the time this model was first proposed, sensation and perception were conceived of in terms of passive registration (sensation) and organization (perception) of information from the environment from which an internal representation of the external world could be generated (cognition). Sensory buffers were conceptualized as modality specific and include visual (iconic) and auditory (echoic) storage. Buffers for other sensory systems were rarely considered in models of cognition, although it is well known that odours can serve as potent cues for memory and emotion (Herz &

Engen, 1996) and other sensory systems are likely to play an important role in future simulated and augmented technology environments. The different time course associated with stimulation of different sensory systems is also rarely considered but has significant implications for sense-making. For example, many odour cues exist over a long time frame (minutes, hours, days), whereas acoustic information is transient and the auditory system is exquisitely sensitive to fine temporal distinctions (in the millisecond and microsecond range). Touch, pressure and pain can be fleeting or long term, but the somatosensory (body sense) system includes active touch (haptic information derived from exploration of the environment by, for example, the hands and feet), proprioception (knowledge of joint angles and positions), kinaesthesia (movement of the body) and vestibular information (information about balance derived from the semicircular canals and otolith organs of the inner ear).

Visual stimulation is the only form of stimulation that we cannot self-generate: it arises from disturbances in the light medium in which we exist, but we do not emit or generate light ourselves. Without a light source, we are unable to see. Perhaps given the reliance of this sensory system on exogenous stimulation, vision is not only our primary sensory system for interpreting the external world, but perhaps also our most malleable. The possibility that its exquisite capacity for pattern recognition imbues vision with its sense of primacy may have intriguing consequences for perception and perception-action coupling in future technology environments.

Perception

Perception refers to the process by which the brain selects, organises and interprets sensory information. Most cognitive psychology or human factors textbook versions of perception focus on visual perception, with much less detailed analysis of other sensory systems if they are mentioned at all. This signals the pervading view that humans are visually dominant, such that for humans “seeing is believing”. However, to understand the impact of future technologies environments on human performance, it is important to have a much deeper understanding of sensory processing and perception than the common textbook approach. The 2.5D Sketch of Marr (Marr & Poggio, 1979; Marr, 1982/2010) proposes three levels of analysis for vision: the computational level; the representational level; and the physical implementation level. Each of these domains is deep and complex. The computational level is largely the domain of physiologists, mathematicians or engineers. The representational level is largely the domain of psychologists and philosophers. The physical implementation level is the domain of neuroscientists and computer programmers/engineers. Computational vision seeks to understand the computational foundations of vision for image processing applications and to help design machines vision systems for a variety of context including science, entertainment, manufacturing and defence and is agnostic in terms of physical implementation. However while successful models in terms of computational vision are proof-of-concept that a particular form of analysis can produce functional outcomes, they do not necessarily speak to the neurobiological implementation of the human visual system. The degree to which perceptual systems (both human and machine) are modular and accessible to conscious scrutiny (see Fodor, 1983, for a specification of modularity in this context) is rarely considered in the applied domain. However the transparency of information processing and its products is a critical consideration for assessing the impact automation, control and autonomy in future technology environments (e.g., Parasuraman & Riley, 1997). Understanding the differences in underlying processing mechanisms and internal system representations is crucial for human-machine interoperation.

While a detailed discussion of the extensive literature on human perception and computational vision (e.g., Lauwereyns, 2012; Nixon et al., 2012; Stone, 2010; Stone, 2012; Werner & Chalupa, 2013) is beyond the scope of this report, the psychological notion of perceptual constancy is important to highlight. Perceptual constancy refers to the fact objects and environments are perceived as a relatively stable in terms of features such as size, colour and shape despite the fact that the physical stimulus energy giving rise to such percepts can change dramatically. The concept of perceptual constancy is important in context of future technology environments. Unlike machine sensors, human sensory systems do not record direct stimulus energy at the receptors, but rather, transduce stimulus energy into neural energy to support human behaviour. For an example in terms of stimulus encoding, the auditory system does not measure sound intensity in terms of decibels but rather, registers sound intensity in terms of the psychological construct of perceived loudness (e.g., Moore, 1989), which is interpreted against the background sound environment (ambient noise level). For a further example, but this time in terms of action outcomes or behaviour, imagine a soccer ball being thrown to you from a distant shaded area of the garden to the sunny area in which you are standing. The ball does not appear to become larger, change colour, or change shape or change in terms of its perceived affordances (to kick it or catch it at an appropriate point on its trajectory) despite the fact that the projection of the ball on the retina is constantly changing, and the ambient visual environment of the ball is also changing.

Perceptual constancy (Day & McKenzie, 1973; Ittellson, 1951) highlights that perception is not only driven by bottom-up, data-driven processing that emphasises the role of sensory information in shaping perception, but is also influenced by top-down schema-driven processing where prior experience and expectations are imposed on raw stimuli to influence perception. Most importantly for future technology environments, it must be recognized that we do not have conscious access to how data-driven and schema-driven processing interacts to produce a given percept, and we do not know how the perceptual range is calibrated relative to ambient energy levels at any given time to allow direct comparison of sensory stimulation or perceptual processing in different scenarios. As can be demonstrated with perceptual illusions such as ambiguous figures (e.g., the Necker cube, see Figure 2 originally reported by Necker, 1832), we can only experience one interpretation of a given stimulus configuration at a time and the rate of switching between different interpretations of ambiguity does not appear to be under voluntary control (e.g., Kornmeier & Bach, 2003; Korneier, et al., 2009; van Ee et al., 2005).

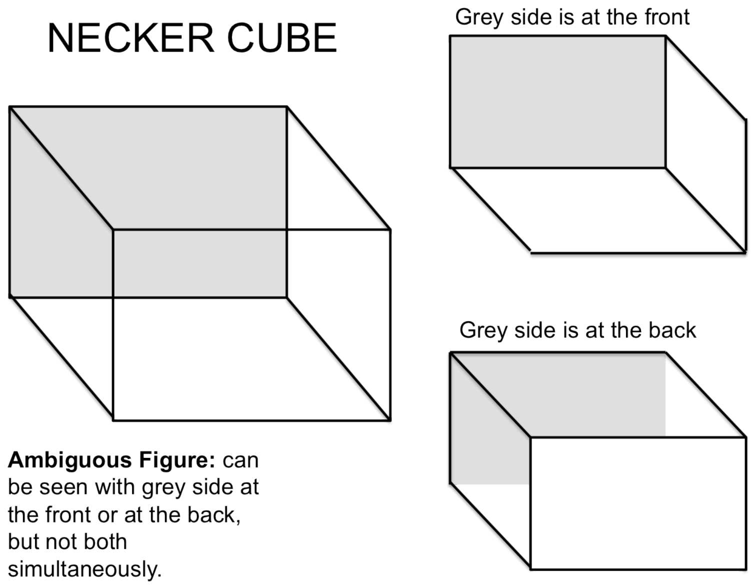

Figure 2. Ambiguous figure: the Necker cube (left panel of illustration) is an illusion of depth whereby the "wire image" cube can be interpreted with the grey side being closer to the viewer (unambiguous version in top right panel), or further away from the viewer (unambiguous version in bottom right panel).

Short Term Memory

In the Atkinson and Shiffrin model depicted in Figure 1, short term memory only holds a small amount of information in consciousness for a short period of time (i.e., 20-30 seconds) unless effort is invested to retain it for longer. It is widely reported that this limited capacity of short tem memory is approximately seven pieces of information, with a normal range of five to nine items (e.g., Miller, 1956; Baddeley, 1994). According to the model, individuals exert some degree of voluntary control over what information is stored and how long it is stored for through the rehearsal process (see Figure 1) which can be used not only to reestablish an item in short term storage, but also to strengthen its encoding in long term memory. Individuals can also chunk information together by organising it into meaningful units, which serves the purpose of reducing the number of pieces of information to retain in short term memory. What constitutes a meaningful unit is difficult to articulate clearly, although common examples would be symbolic codes like phone numbers, postal codes and established acronyms, or the slightly more nebulous information stored in schemas.

Working memory

Inspection of Figure 1 suggests that consciousness to some extent derives from paying attention to sensory information, or from recalling stored information so that it is "re-activated" in the short term store. The active role of short term memory in processing new information as well as recalling relevant information from long term memory, prompted Baddeley and Hitch (1974) to reframe short term memory as working memory. Working memory was conceived of as a place for temporary storage and information processing including the evaluation and manipulation of information. The notion of working memory has continued to evolve over time. According to Baddeley (2000), working memory comprises four components, including 1) a central executive; 2), a phonological loop; 3) a visuo-spatial sketchpad; and 4) and an episodic buffer (see **Figure 3**).

The central executive is conceptualized as a modality-free, limited-capacity component of working memory that controls and manipulates information from the other components. It is associated with processes such as rehearsal, reasoning, and decision making related to completing two simultaneous tasks, and is considered the most important component (or resource) of working memory. It also the most problematic in conceptual terms in the sense that it inherently invokes the concept of a "homunculus" (see Yeung, 2010) – a little man-in-the-head" who controls the action of working memory, which itself is supposed to be controlling the action of the person in whose head the homunculus resides. Presumably the homunculus also has a form of working memory, with its own homunculus, setting up an infinite regress, and no proper explanation of the central executive of the original homunculus.

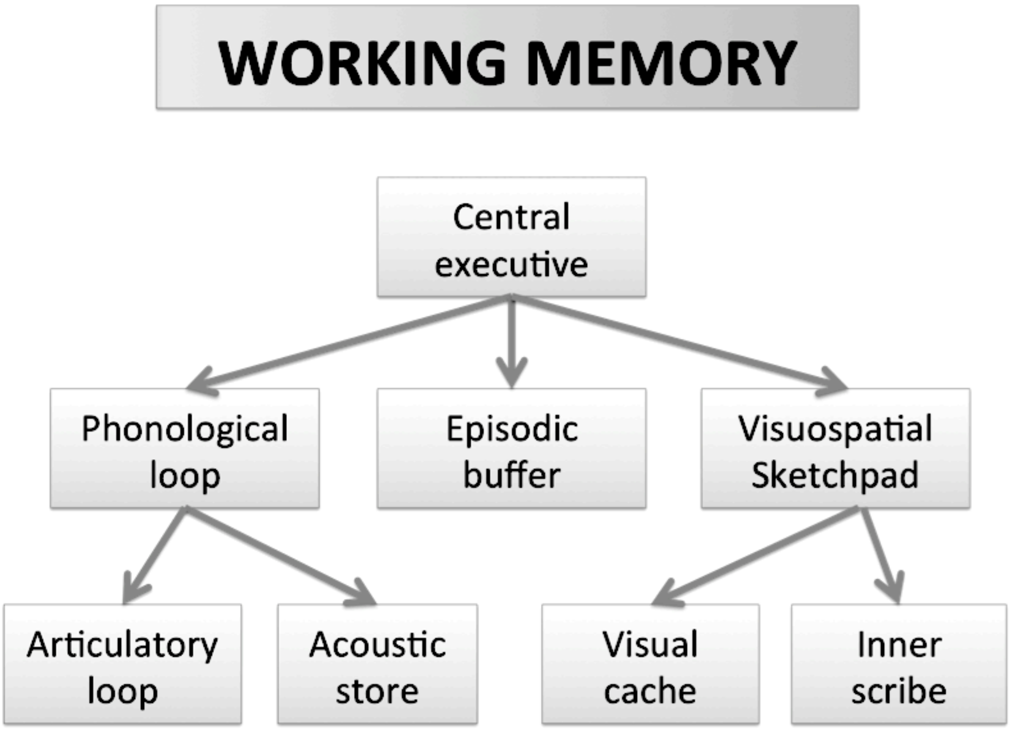

Figure 3: Model of key components of working memory

The phonological loop is another proposed component of working memory that deals with sound-based information including preserving the order of words used in speech. According to Baddeley et al. (1990), it has both a passive phonological component concerned directly with speech perception, and an articulatory component, concerned with speech production. In contrast, the visuo-spatial sketchpad is postulated to store and manipulate visual and spatial information about the location and nature of objects in the environment. Logie (1995) argues for two sub-components of the visuo-spatial sketchpad, a visual cache that stores information about form and colour, and an inner scribe that processes spatial and movement information. The episodic buffer is a fourth component of working memory that is used to integrate and briefly store information from the phonological loop, the visuo-spatial sketchpad and long term memory.

More elaborate models of working memory have been proposed by Cowan (1995) and Ericsson and Kintch (1995), in which they expand the notion of working memory to include activated regions of long term memory that are indexed to provide fast access to schemas. Oberauer and others take a different approach (Ecker et al., 2013; Ecker et al., 2014; Kessler & Oberauer, 2014; Oberauer & Kliegl, 2006; Oberauer & Bialkova, 2009; 2011; Oberauer & Hein, 2012; Öztekin & McElree, 2010) in expanding the notion of working memory to include both declarative and procedural elements, and their approach to understanding working memory will inform our own research program and experimental approach.

Long Term Memory

Whilst some information stored in short term or working memory may be lost due to decay over time or interference from competing additional information, other information moves to the long term memory store where it can reside for very long periods of time, and where the storage capacity is presumed to be virtually limitless. Information assumed to be stored in long term memory includes two primary kinds of information, declarative and procedural. Declarative memory refers to the memory of facts (semantic memory) and specific events (episodic memory), or information that can be stated or declared by an individual (Tulving, 1972; 1987). Procedural memory refers to how to do things (e.g., motor skills) and is thought of as an automatic, implicit, non-conscious form of processing, however it is also possible to render this type of information explicitly, suggesting that the general steps of an action or procedure can be made explicit (consciously available).

The method by which implicit procedural information becomes explicit is not easily explained but is pivotal to the understanding the development of skilled performance, automaticity and expertise. The epistemological question is whether explicit knowledge of procedural information is constructed by reflective analysis of inputs and outputs ("I kicked the ball to that player [output], because I saw he was in a better position than the other two options [input]"), or by some method of introspection that permits conscious access to actual procedural processes involved in sensing, perceiving and interpreting visual information, considering in terms of football-oriented schemas, and making the decision. Fodor's extreme version of modularity of mind (Fodor, 1983) suggests that perceptual modules are cognitively impenetrable (not available for conscious inspection), suggesting that we can only reconstruct what we do ourselves using the same cognitive processes or theory of mind (Baron-Cohen, 1995) that we use to interpret someone else's behaviour (Curruthers, 2009), albeit from an egocentric rather than an allocentric perspective.

The process for recovering information from long term memory is called retrieval, which involves bringing information from long term memory back to short term or working memory. As can be seen from Figure 1, the mode of forgetting that occurs in long term memory is that of interference, suggesting that forgetting is a result of faulty encoding or a failure of retrieval rather than the result of decay of storage. In the context of the virtually limitless storage capacity offered by current and future technologies, it is important to highlight that "forgetting" is an issue of encoding and retrieval, not of storage space. The importance of appropriate forgetting (for example, updating incorrect information, deleting outdated information, removing information that is no longer relevant, reanalyzing all the assumptions based on updated or deleted information) cannot be overstated (see for example, Anderson, 2003; Ecker & Lewandowsky, 2012; Glanzer et al., 1991; Koriat et al., 2004; Roediger III et al., 2010; Wixted, 2004; 2005), and will become a massive issue in the future world of "big data" and "the quantified self" (e.g., see Mayer-Schönberger & Cukier, 2013; Nafus & Richards & King, 2013; Sherman, 2014; Swan, 2013).

Models of Attention

The process of encoding sensory information into short term or working memory is represented in Figure 1 in terms of a selective filter model of attention (e.g., Broadbent, 1958). Broadbent's selective filter theory of attention drew heavily on the information processing capability of the recently invented computer systems of the time, comparing limited attentional resources of humans to the limited central processing capacity in computers.

Broadbent's strict 'early selection' theory was not supported by later studies (e.g., Moray, 1959; Treisman, 1964; 1969) and Treisman (1964) proposed a threshold approach to early filtering whereby contextually important stimuli in unattended streams, such as an individual's name or warnings of impending danger would be break through the filter. In contrast, Deutsch and Deutsch (1963) proposed a late selection model in which all information is processed in short-term memory where it is segregated into different channels, such that only the most important channels will be attended.

Kahneman (1973) notes that attention is not only selective, but also involves intensity or effort, which, like information processing resources, is of limited capacity (see **Figure 4**, where the wavy line indicates available attentional capacity within a pool of more generalised arousal). The important elements of this model are the dynamic levels of attention and arousal, along with the allocation policy that determines what will be attended. Kahneman proposes four factors that influence the allocation policy. Enduring dispositions reflect the rules governing involuntary attentional capture by peripheral or sudden stimuli. Momentary intentions are the voluntary activities engaged in on a moment to moment basis. Evaluation of demands occurs when concurrent activities call on more capacity than is available. The fourth factor is the effect of changes in general arousal, which affect the way in which attention is allocated, and also how much energy is available in the attentional pool. Kahneman's model was intended to complement rather than replace models of information processing such as the information flow model presented in Figure 1, and he notes that, in contrast to such models, his model is a control diagram that describes the influences and interactions of different components of the system.

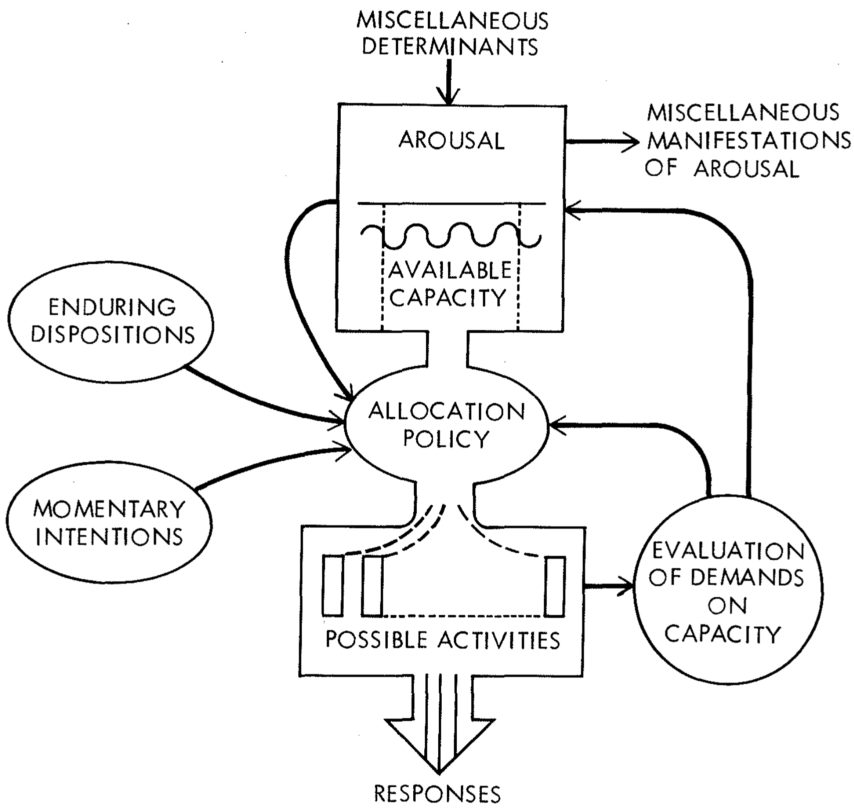

Figure 4. A control diagram of the capacity model of attention. See text for further description. Taken from Kahneman, 1973 p 10)

The aspect of Kahneman's model that we highlight is the fact that attentional capacity varies both in relative terms (how much available attention can be allocated to a given activity) and in an absolute sense (the size of the attentional resource pool changes based on arousal levels. This poses some difficulties in terms of conceptualising the quantitative structure of "attention", and in comparing data from different contexts.

Young and Stanton (2002a; 2002b; 2007) identify the dynamic aspect of attentional effort, which they describe in their malleable attentional resource theory. They note that the limits of attentional capacity can change in the relatively short term, depending on task circumstance, through malleable attentional resource pools that operate as a form of gain control over arousal. Young and Stanton proposed that skill and mental workload are inversely related such that, as skill improves on a task, attentional resources are released for other tasks, with a consequent decrease in mental workload. Young and Stanton found that driving performance is very much resource-limited for novice drivers (i.e. performance decrements are a consequence of limited cognitive resources), but data-limited for expert drivers (i.e., performance decrements are associated with insufficient data rather than lack of cognitive resources to process the data). While novices receive a benefit from automation, experts do not, due to the resource-free nature of their processing. It is important to note that these data speak only to immediate task performance, but are often misapplied within training contexts. Novices who undertake complex tasks with the aid of automation may not end up learning the cognitive skills required to support future expertise, particularly if the pathway to improved performance is through learning to allocate attentional resources appropriately.

Selective Visual Attention

While the early research on attention (e.g., Cherry, 1953; Moray, 1959; Broadbent, 1958) was conducted with auditory stimuli generated by cutting and splicing tape-recorded acoustic signals, the advent of modern computers in the 1980s allowed for well-controlled computer-based visual presentation of stimuli. The shift in sensory modality from studying auditory attention to studying visual attention was most likely motivated by the ease of stimulus generation rather than by any consideration of the inherent differences between the two modalities. However, it is important to note that, while audition is inherently a time-based sensory system, vision is inherently a spatial modality and therefore has different attentional properties and requirements.

Posner (1980) investigated the processes and mechanisms underlying visual attention. He recognised two visual attention processes, overt orienting, where focal vision is directed towards objects and locations through head and eye movements and covert orienting using peripheral vision. While covert attention is recognised as being important in visual anticipation and target selection in skilled performance, most measures of attention are measures are assumed to be of overt attention based on direction of gaze. It should be noted that, while direction of gaze indicates the current focus of central foveal vision, covert attention is likely to reflect the processing of anticipatory cues in peripheral vision, and these anticipatory cues are likely to be critical elements in social and tasked-based interactions (e.g., Bertenthal & Scheutz, 2013; Lauereyns, 2012) and in skilled decision making (Hagemann, et al., 2006; Savelbergh et al., 2002; Williams & Ericsson, 2005; Williams et al., 1999).

Typical Posner tasks (Posner, 1980; 2014) use an experimental design in which participants detect a briefly presented stimulus as quickly as possible while fixating on a central point. Two types of cues may be presented prior to the stimulus, a central spatial cue (e.g., an arrow pointing left or right) or a peripheral spatial cue (e.g., an illuminated box in the location of the upcoming target, or a sound signal from the appropriate location). Cues can be valid (congruent with the location of the upcoming target) or invalid (not congruent with the location of the upcoming target) and the percentage of valid to invalid cues can be varied across a block of trials. Typically, reaction times to stimuli in trials where cues are valid are faster than uncued trials, whereas reaction times to stimuli in trials where cues are invalid are longer, suggesting not only a facilitatory effect of valid cues but also an inhibitory effect of invalid cues (Awh & Pashler, 2000; Lachter et al., 2004; Posner, 1980; 2015; Posner et al., 1980). Furthermore, when invalid cues are more frequent than valid, central cues are often ignored but invalid peripheral cues (an illuminated box in a location incongruent with the upcoming stimulus) still negatively affect performance.

The findings from this paradigm led Posner (1980) to propose two different types of visual processing, endogenous top-down processing and exogenous, data-driven, bottom-up processing. Posner suggested that the endogenous system operates via an individual’s expectations and intentions whereas the exogenous system is reflexive in nature and responds to salient stimuli that occur in peripheral vision (Posner, 2015 although see Restic & Kingstone, 2012).

Summary

The preceding account of memory and attention articulates the known phenomena that require explanation, and seems to progress by adding new components to accommodate new research findings. It does less well at providing further insight on how we represent information from the world, if indeed we do. Questions of whether short term and long-term memory respectively refer to processing, storage or indeed to the type and duration of experimental task, abound in the literature (e.g., see Craik & Lockhart, 1972), as do questions regarding the nature of capacity limitations of memory and attention, but the models of memory implying hierarchical memory stores or levels of processing remain in vogue.

The main problem with the information processing approach is the degree to which it is embedded in the technology metaphors of the time (Gigerenzer & Murray, 1987). Visual information is conceptualized in terms of successive static images from a camera (snapshots acquired at each visual fixation) rather than in terms of a dynamic information stream driven by sense-making requirements at the time. Until very recently, computers were very much capacity-limited in terms of the information processing that could occur in the central processing unit. However the multiple processing streams required not only for different aspects of visual information, but also for multisensory information from pertaining to objects and events, give rise to massive "correspondence" issues in terms of integrating related information, problems that seem relegated to the sensory buffers or the central executive.

This correspondence problem is also evident in the world of "big data", which provides new metaphors for describing human cognition. For example, there are now highly sophisticated algorithms for matching information about a hypothetical John Smith from financial records, employment records, social security information, web browsing history and the like. However when matching data from multiple sources, there can be mismatches in the attributes and properties recorded, the meaning of different attributes in different contexts, and there can also be errors or missing data in records, some of which are filled with default information, some of which are empty, and some of which are plain wrong. It is not always possible to trace the origin of false information or to understand the implications of that false information in future decision making. Human perception and memory can be said to deal with similar issues in terms of the data it uses to construct its understanding of the world.

While it could be argued that no scientist in the field truly believes in the simple information-processing models of cognition found in many textbooks, such models continue to dominate cross-disciplinary research and practice due to their ready conceptual accessibility and concomitant ease of application to real world scenarios.

The modern cognitive science literature, incorporating rapid advances in neurobiology, information and communication sciences and technology to our understanding of psychology, is really difficult to integrate into a coherent model of human cognitive capability. There is much common terminology, but the terminology does not always align across different areas, such that the same words refer to different concepts, or there are different words for similar constructs.

Multiple Resource Theory

Meanwhile, the pragmatic approach to cognition adopted in many human factors contexts does not attempt to distinguish between different theoretical constructs such as attention and working memory, but instead considers cognitive resources more broadly in terms of multiple resources used in information processing (Wickens, 1980; 1984; 2010). The common theme among multiple resource models is that cognitive resources from a limited resource pool can be prioritised and allocated as necessary to meet various task demands. Resources will be allocated to a task on the bases of task difficulty, the level of performance required, and the priority of the specific task within the current task environment. The resources that remain ("spare cognitive capacity") can then be allocated to other tasks.

The influential multiple resource theory multiple resource model described by Wickens (Wickens (1980; 2002; Wickens & Liu, 1988) has four dimensions, each of which is claimed to be associated with distinct physiological processes (see Figure 5).

The first dimension is that of processing stages, which can be at a perceptual level, a cognitive level, or a response level. The second dimension is based on the perceptual modality of input (illustrated in Figure 5 by visual and auditory modalities. The third dimension of the model is that of processing codes, which are purported to differentiate between analogue, spatial processes and categorical, symbolic processes Wickens (1980; 1992). The fourth dimension of the model distinguishes between focal and ambient processing, represented in Figure 5 by the oval (focal) on the shaded side of the cube (ambient). The multiple resource theory has been complemented recently by a model that governs the allocation of attentional resources in real-world environments (Wickens, 2006). This model involves four components: Salience, Effort, Expectancy and Value (SEEV model, see top-right panel in Figure 5). Salience and effort are associated with data-driven attentional processes, whereas expectancy and value are associated with schema-driven top down processes.

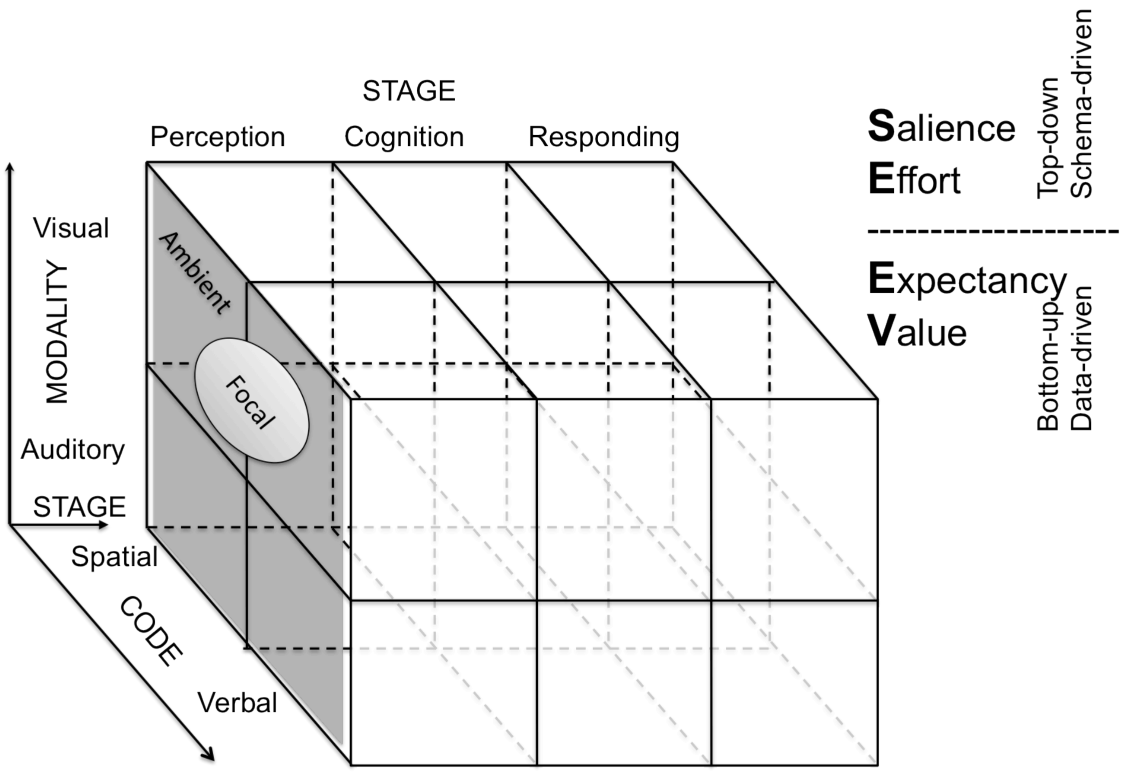

Figure 5 Multiple Resource Theory (adapted from Wickens, 2002; 2006)

As with information processing models of human cognition, the multiple resource model extended by the SEEV model provide a descriptive framework supported by a human factors evidence base from specific task environments, as is required by the applied world. It does not provide an adequate conceptual framework to guide or interpret scientific research, nor does it provide a sufficiently robust platform for understanding the implications for human of future technology environments.

Situation Awareness

In parallel to the development of multiple resource theory, the three-level construct of situation awareness was introduced to the human factors domain by Endsley (1995; 2015a; 2015b). While the concept was initially met with scepticism (Flach, 1995; 2015), there has been an abundance of research using the situation awareness construct over the past twenty five years. Wickens (2008) provides overview of the widespread application of the construct in human factors measurement, training, error analysis, teamwork, automation and workload. Endsley and Jones (2012) provide guidelines for design of systems to support situation awareness and for training programs to enhance the cognitive processes and mechanisms that underlie high levels of situation awareness. Wickens argues that the popularity of situation awareness as both a theoretical construct and applied framework justifies its ongoing viability (Wickens, 2015) despite serious concerns that it misleading, confusing and has outlived its usefulness (Dekker & Hollnagel, 2004; van Winsen & Dekker, 2015). Widespread use of a proposed framework does not ensure that the underlying model has theoretical validity in the psychometric sense (see section on Reliability and validity, p 11 of this report).

Parasuraman, Sheridan and Wickens (2008) catalogue a strong body of empirical research using the construct, and the list is, indeed, quite impressive. Situation awareness provides a framework for perception, comprehension and projection as the three levels of situation awareness (as per the Situation Awareness box of Figure 6). It incorporates goals and goal-directed processing in directing attention and interpreting the significance of perceived information while also allowing salient information capturing the state of the environment to direct attention in a data-driven fashion. The interactions and feedback loops within the system model of situation awareness can accommodate the importance of alternating goal-driven and data-driven processing and the role of expectations and schemas.

In fact, over and above the inherent linearity of the model in terms of stages, the major problem is that the model is so all-encompassing that it provides no useful analytic clarity. Few will disagree with the notion that being aware of the demands of the situation as it unfolds (situation awareness) is critical to performance in many complex and dynamic domains of expertise. However it can also be argued that situation awareness plays a critical role in every form of cognitive performance measure and evaluation and, as depicted in Figure 6, it appears to mediate the entire cognitive processing chain from sensing the environment to decisions and actions.

Furthermore, by treating situation awareness as the knowledge that leads to decision making, and decisions as outcomes of a situation assessment process, ignores the problem that decisions themselves rarely encapsulate the information leading up to them. So knowing the decision outcome provides “closure” on that iteration of situation assessment without necessarily providing any of the system information required to understand the reasons for a decision, which may still be relevant to making other contingent or contiguous decisions. The transparency of situation assessment leading to decision making is an important consideration in terms of automation, and distributed situational awareness within teams and across systems.

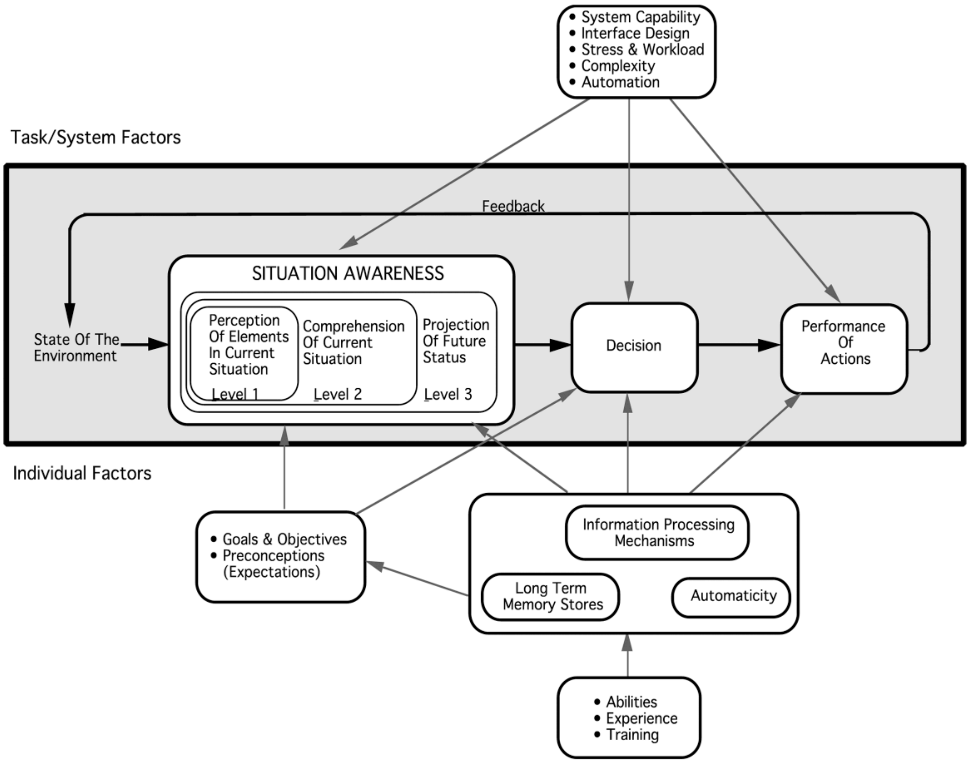

Figure 6 Model of Situation Awareness in dynamic decision making originally from Endsley, (1995) and reproduced from Endsley (2015)

It should be noted that the shift from Endsley's three-level framework of situation awareness to a distributed systems approach as proposed by Stanton, Salmon and colleagues (Stanton et al., 2006; Stanton et al, 2015) among others (e.g., Chiappe et al., 2012a; Chiappe et al., 2012b; Chiappe et al., 2015; Fioratou et al., 2010; Gutman & Greenberg, 2001; Hollan et al., 2000; Hutchins, 1995) is a major shift in theoretical (philosophical) approach to knowledge representation. Indeed such a shift raises fundamental questions at the philosophical level of whether representation is the correct frame of understanding human cognition. These theoretical distinctions can be treated dismissively by people operating in the applied domain with "real world" problems to deal with, however they are of critical importance in guiding future directions in an era of new socio-technical complexity and an impending integration of human with machine, and particularly in the context of the emergence of potentially autonomous systems. We have neither the agreed-on conceptual frameworks within cognitive science nor the ethical frameworks within broader society to deal with distributed cognition and autonomous decision-making in mediated social interaction with humans (e.g., boyd, 2014; Turkle, 2011; 2012) let alone with “intelligent” machines (Minsky, 1988; 2007; Rhodes, 1986; Turkle, 2007). Endsley’s three-level model of human-cantered situation awareness provides no further insight into these complex problems, but human factors models of distributed cognition and distributed situation awareness are similarly grounded in specified task environments and systems.

Information Processing Models and Representation

Information processing models of human cognition all rest on an empiricist, representational view of human cognition. While cognitive constructs from these models, such as attention (e.g., Broadbent, 1958; Kahneman, 1973), mental workload (e.g., Wickens, 2002; 2010) situation awareness (e.g., Endsley, 1995; 2015) and its variants (e.g., Salas et al., 1995; Salmon et al, 2010) have been very useful in refining human-machine interactions in existing task environments and have spawned a wealth of human factors research, this report argues that they are not sufficiently robust for understanding implications of future technology environments. Distributed situational awareness (Stanton et al, 2006; Salmon et al., 2009) provides a more flexible framework that acknowledges complexity at a systems level, but is still founded on a pragmatic adoption of cognitive models such as schemata (e.g., Bartlett, 1932; Neisser, 1967), and less cognitively-based notions of perception-action cycles (e.g., Neisser, 1976; Stanton et al., 2009) rather than committing to, or offering, a fully-elaborated scientific model of cognition across human and machine agents.

It is important to emphasise that the information-processing view of cognition has been strongly contested at a philosophical and conceptual level. For example, recent contributions to the literature (see for example, Flach, 2015; Hoffman, 2015; Stanton, 2015) echo many earlier and ongoing debates in philosophy and psychology (Merleau-Ponty, 1945/2013; Minsky, 1988; Neiser, 1976; Varela et al, 1992) regarding the essential nature of perception and cognition. In contrast to the information-processing, representational approach presented in psychology and human factors textbooks, proponents of phenomenology (focusing on experience of the world rather than representation) and embodied cognition question the need for a representational level of cognition at all (e.g., Varela et al., 1974; Varela et al, 1992). The notion of ecological perception (Gibson, E., 1969; Gibson, J 1979) and the perception-action cycle (Neisser, 1976) is based on a direct interaction with "the world" without need to first represent the objects within it. Phenomenological experience is considered to be direct, such that meaning resides not in the representation of the world, but through interaction with it, hence the embodiment of cognition through interaction. The phenomenological approach is coming back in fashion as researchers try to deal with the complexity of human interactions with ecologically-valid real-world environments. With the additional complexity introduced by imagined future human-machine environments (see Minsky, 1988), the phenomenology of "being a machine" may well become important in terms of ethics and decision making in the future development of autonomous agents. It is beyond the scope of the report to discuss the different philosophical perspectives in detail, but we strongly contend that these philosophical and conceptual issues must be adequately addressed when considering the implications of a future technology landscape. Autonomy, awareness and augmentation all have associated philosophical and ethical issues that bear on future scenarios (Dekker, 2013; Grote et al., 2014; Parasuraman & Miller, 2004; van Winsen & Dekker, 2015). Indeed, the science fiction industry provides ample creative manifestations of these issues in projected futures where the practical constraints of current technology and culture have been relaxed, and these future scenarios must be investigated more scientifically.

Future research directions

The predominant empiricist view that underpins textbook models of cognition describe the role of perception as interpretation of external stimuli to create a model or representation of the external world inside our heads from which our cognitive system can make meaning. Alternative views, of direct perception (e.g., Gibson, E., 1969; Gibson, J., 1979), embodied cognition (Jeannerod, 2006; Johnson-Frey, 2003; Noe, 2006; Lauwereyns, 2012; Prinz et al., 2013; Varela et al, 1992) and autopoeisis (Maturana & Varela, 1973), describe perception in phenomenological terms (Merleau-Ponty, 1945/2013) that require no further explanation – we perceive meaning / affordances directly through our interactions with the environment.

There are many footnotes in empiricist descriptions of perceptual and cognitive processing that emphasise the role of top-down processing in guiding our interactions with the world, and the dynamic nature of situations that have been studied somewhat statically. However most such footnotes do not really address the fact that the dynamical nature of action and interaction may be its most important quality. If meaning derives directly from our dynamic interactions within a dynamic environment, one of the most important aspects of generating meaning is to identify the coupling points of our perception-action coupling (the affordances for interacting with other agents and resources, including human, non-human and machine agents). Identifying affordances is a shift in conceptualisation of perception away from object recognition and veridical environmental representation towards a focus on interpreting patterns of stimulation in terms of future actions and reactions.

Such a reconceptualisation of perception, cognition and perception-action coupling is by no means new in philosophy, psychology and theory, but has not really been adopted within human factors. Norman and Verganti (2014) discuss incremental versus radical innovation and note that human-centred design (the most focussed on affordances and user understanding of systems) is most successful in incremental innovation, or improving existing machine interfaces. Moray (2006) notes the difference between human factors research aimed at solving specific problems in design and research aimed at understanding theories of cognition. These authors identify that most successful human factors and cognitive engineering exercises are undertaken in the context of a specified existing system or in the context of developing a new system to undertake a known task. Action research is undertaken guided loosely by a theoretical framework to provide the evidence for evidence-based practice. The theoretical framework provides a shared language through modelled constructs to guided multidisciplinary practice and the outcome (new system) is the “proof” of the approach.

There appear to be two notions of applied research: one is that applied research should operate within an action research model, undertaking research to solve specific problems in the domain of practice, using an analyst model (Stanton et al Human Factors methods). The second is to apply scientific theories into domains of practice in a way that tests the legitimacy of the scientific theories themselves, as well as contributing to the domain of practice. In known task contexts (e.g, Design a new interface to control two UAVs), while the specific design requirements are for a future task environment, the functional requirements can be specified in terms of known parameters of current tasks and environments. However, in considering new interfaces in the context of new types of machines, or new types of human machine interaction (Avatar, bionic limbs), the parameters and constraints of current task environments need to be reconceptualised. In Norman and Verganti’s (2014) terms, radical innovation is required.

The identification of human performance capabilities, both physical and cognitive, have until now been conceptualised in terms of a technical specification of tolerances, areas of peak performance, and consideration of graceful degradation rather than catastrophic failure in both physical and cognitive parameters. In order for measures to be validated, we search for accuracy and reliability of objective metrics. However, a hugely important design consideration in terms of human sensory systems is the role of adaptive gain control, which allows sensory receptors to code a wide range of sensory stimuli relative to a background. The output of the sensors in our sensory systems does not give an objective measure of the stimulus property being encoded (i.e., the absolute pressure of a somatosensory stimulus, or the absolute intensity of a sound, or the absolute RGB registrations of light) but rather, gives a relative measure of the attended stimulation (a focal view of the stimulus space) calibrated by an ambient view of the overall stimulus space. It may also be that the primary goal of the perceptual system may not be to identify objects in the environment, as much as to identify affordances in the environment for interaction. In this sense, the task environment will reprioritise affordances in terms of meaning and desired functional outcomes. But the “reality” of the environment may not rest in its physical existence as much as in its opportunity for interactivity. It is important not to confuse dynamic environments with interactivity - the important feature may not be the degree to which the environment is changing, but more, the degree to which we can interact with an environment to effect change (our ability to change the environment). The construct of an affordance encapsulates the idea of "an opportunity to interact" being the key motive of perception. Visual object identification for the most part, offers opportunities for retrieving prior notions of affordance. Schemas offer prior configuration of past affordances to maximise certain aspects of interaction. Cognitive affordances may signify the opportunity for interaction at a conceptual level – for example, learning a new language may involve translating words from one language to another (thereby constraining the affordance of the new word by the ties to the old word) or may be undertaken through "immersion". Immersion may create a better environment in which to understand new affordances for interacting with other humans which we can describe as different nuances or new concepts that cannot be expressed in the other language. Maturana (Maturana & Varela, 1973; 1987/1998) created the word "autopoeisis" to create a new construct that would be misinterpreted by tying it to the conceptual baggage of existing words. Pylyshyn offers the concept of a proto-object (Pylyshyn, 1989), but Fodor and Pylyshyn (2015) both note the problem of trying to discuss concepts for which there is no current word.

The implications of human capabilities and performance for future technology environments may require a reconsideration of human capabilities for interaction with their environment. The dominant empiricist approach to human cognition and technology operates on the basis of an objective "real world" out there that can be perceived veridically via human or machine sensor. However the notion of perception-action coupling and affordances for interaction as the source of "meaning" suggests that there may not be as much distinction between the "real world" and the "virtual world". In the same way that we can incorporate tools into our perceptual frame, such that we distribute our perception and cognition to integrate the tool within our representation of "Self", if interactions within the virtual world offer social and other forms of meaning, their intrinsic meaning patterns will offer affordances whereby we can directly interact with those information streams.

It is already the case that the visual patterns of information on a radar screen, or on the monitor during laparoscopic surgery offer affordances and meanings that may not be mediated by translating through specific representations of their "real world" referents. For example, an air traffic controller may be more interested in the trajectories of aircrafts than anything about the aircraft itself. Indeed an object that moves like an aircraft and has the mass of an aircraft will have the same affordance as a projectile in terms of maintaining aircraft separation. However, the aircraft trajectories in air battle space have different "affordances" and these need to be incorporated into the meaning attributed to these objects. While in terms of specific task actions, it is important to ID the object associated with the trajectory and communicate with its pilot, the perceptual/cognitive interpretations and interactions are in terms identifying trajectories and communicating with pilots.

The "view" in terms of affordances and meanings for the pilot in an aircraft are different from those of a drone pilot on the ground. However, in most task analyses, the parameters of importance in terms of objective performance measures will be to do with mental and physical workload and controlling the aircraft with respect to its flight path and mission, without due consideration for the possibility of fundamentally different conceptualisations of the environment by all involved due to the different perspectives and different affordances for interaction arising from different locations and information sources.

As noted by Norman (Norman & Verganti, 2014), even as one of the founders of human-centred design, this approach while well suited to incremental improvements in design, is not a good model for radical innovation. Radical innovations in technology produce new environments to which humans adapt (which is the hallmark of human capability). The way in which they adapt then focuses the human factors researchers on how to optimise the human-machine interface. This is not to say that all technologies will be adapted to and that designers of technologies should not keep human capabilities in mind. Rather, innovative technology and radical changes in technology and interactivity will produce adaptations that we may not be able to conceive of given that we have not had an opportunity to experience the possibility of unimagined affordances. The socio-cultural approach to tool use of Vygotsky (1980) notes the fact that new tools will be adapted by human users to fulfil their needs for interaction with the environment, and may offer affordances unimagined by the inventors of the tools.

Virtual environments, autonomous agents and automated systems may be better conceptualised in terms of the affordances for interaction that they offer. Problems with automation may arise through the lack of coupling points for human-machine teamwork. Problems with human teamwork may arise when tasks and roles become too specific, so that there is no shared view of the system or task as a point of coupling/interaction. Attempts to make autonomous agents align with conventions of human interaction to promote greater trust of technology may work like artificial sweeteners – while superficially, the actions promote trust through a cognitive heuristic of similarity (e.g., Gigerenzer & Gaissmaier, 2011), the automatic inferences in terms of affordance and interaction promote deeper problems. In the case of artificial sweeteners, the internal dialogue (at the physiological level not at the conscious level) might be thus: "Sugar is providing me energy? Why do I still feel lethargic? I must need more sugar." and as a result, insulin sensitivity is adjusted in the wrong direction and a reduction in calorie intake leads to an increased perceived need for energy. The analogous internal dialogue (again not at the conscious level) in terms of social interaction with a machine is "This machine understands me. It knows certain things about me, therefore I trust it. I trust it and therefore I expect it to infer (know) other things about me. But wait - why didn't it know the things I expect trusted human collaborators to know? How does it know the things that I don't want trusted collaborators to know (or communicate that they know). It is being unkind / stupid / hostile". The chain of inference relating to trust needs to be reconceptualised to accommodate human-machine interactions in a more transparent way.

There is a strong need to improve the cross-disciplinary communication of theories of human perception, cognition and social interaction to match current understandings that drive the applied world. Scientists need to understand that applied researchers are mostly not interested in new or conceptually challenging theory from the academic world, especially if their current models "work" in the practical world of their domain of interest. The emerging complex socio-technical environments of the near future may lead to radical change in what constitutes the "real world", and may offer many new opportunities for interaction with new conceptualisations of "reality". These radical innovations may generate a strong need a rethink and re-imagine the essential phenomenological experience entailed by "being human".

The need to reconceptualise the sense of human identity is not in any way new (e.g., see Minsky, 1988; Varela et al., 1992; Turkle, 2011; Grote et al, 2014) and underpins many approaches to developing autonomous systems. However many of the current generation of applied researchers and practitioners did not grow up with the same set of assumptions and intellectual challenges as their mentors, and many have not thought of, or transmitted the philosophical questions that ruminated in the thoughts of their mentors, without necessarily being articulated in their scientific writings. The greater questions that more modest research programs aim to investigate do not necessarily find their way into the framing of the specific research experiments examining specific details of broader models, although we hope that the content of the report so far provides insight in the direction of our overall research effort, not just the experimental program funded by this research agreement.

EXPERIMENTAL PROGRAM DESIGN REMOVED FROM THIS VERSION

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