

## Working With Human Thinking In Developing Intelligent Technologies\*

Pertti SAARILUOMA<sup>1</sup>, Antero KARVONEN<sup>2</sup>, Jose CAÑAS<sup>3</sup>

and Jaana LEIKAS<sup>2</sup>

<sup>1</sup>Jyväskylä University, Finland

<sup>2</sup>VTT Technical Research Centre of Finland Ltd., Finland, antero.karvonen@vtt.fi

<sup>3</sup>University of Granada, Spain, delagado@ugr.es

Correspondence should be addressed to: Pertti SAARILUOMA, ps@jyu.fi

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### Abstract

Artificial intelligence and robotics are becoming part of everyday life and work. They tend to support or replace human work in industrial processes, as intelligent artefacts can perform tasks that previously relied on human information processing. To develop smart technologies more successfully as a substitute for human work, they should be developed using research on human thinking, based on the analysis, mimicking and modelling of human thought processes. This paper discusses thought process analysis, i.e., qualitative and quantitative study of thinking, cognitive mimetics, i.e., the imitation of human information processes by machines, and human digital twins, i.e., the computational modeling of human thought processes in the design of new technological solutions. These are discussed as conceptual and methodological tools for the creation of intelligent objects.

**Keywords:** artificial intelligence , thinking, cognitive mimetics, human digital twins

### Introduction

Information is neither matter nor energy (Wiener 2019), but it is nevertheless an important component in improving industrial work today. Traditionally, advances in work have been made in improving materials for example by replacing soft bronze with harder iron, and in improving energy, by overcoming darkness with electric lights (Bernal 1968). Today, information brings a new element to the development of work processes, as understanding information processing opens up opportunities for people to manage work processes intelligently and, for example, support or even replace people with intelligent technical artefacts (Samuels 2020).

Artificial Intelligence and robotics are becoming part of everyday life, both in work environments and in households. In work life, intelligent technologies have become part of the work process in sectors such as education, finance, transportation, healthcare, agriculture, and manufacturing. As the intelligent execution of work processes has become a key element in the development of work life, the conceptual foundations for supporting human activities with new information technologies should be explored in more depth.

Human thinking has played a key role in the development of intelligent artefacts. Humans have the ability to intelligently analyze and control what they do and what happens in work processes and how processes should work. Mostly, learned routines can take care of human actions, but thinking is needed routines are insufficient to achieve the action goals (Newell and Simon 1972). Thinking enables people to find new ways of acting in new kinds of situations.

A most important function of new intelligent devices is to support and replace human thinking in processing information. Transport robots, for example, have taken over the tasks of the errand boys. When delivering shopping to people, they can navigate urban environments and solve their mobility problems on the streets. They may have trouble distinguishing traffic lights when the sun is behind the lights, but they can still solve the problem and find rational ways to reach their destinations. Each time intelligent technical artefacts cope with problem situations, they are able to learn from their actions and become better able to replace human agents in these tasks.

Human reasoning is the capacity that people use to control technical artefacts in novel situations (Newell and Simon 1972). Advancing technologies in thought-demanding situations should benefit from understanding how people process information in such situations. If people can steer a ship from Turku to Stockholm through one of Europe's most complex archipelagos, and have done so over a thousand years, we know that there is an information process, that can take care of the steering process. The problem is that we do not know how people carry out such a tacit task. Indeed, even in ship sailing, the information processing methods that cognition exploits in goal-directed actions are culturally constituted (Hutchins 1995). It is therefore important to learn how to analyze human thinking to facilitate the development of intelligent technologies. In this paper we describe some of the key steps in translating human thinking into intelligent technical processes, that can take care of the same processes.

## **On experts' thinking**

Sea captains, like all professionals, are experts in their work (de Groot 1965). They train for years and acquire information processing skills that enable them to perform their professional tasks. Understanding what experts do may seem simple. One might think that you just ask people to tell you what they do, and you will find an explication of professional performance. However, this is not so easy, because people only partly know what they do and how they do it. Most of human information processing is tacit and subconscious (Revonsuo 2009).

One might think it would be easy to say how people walk upstairs, but it is not. What is the speed and accuracy of human movements on different types of stairs? How do they keep their balance? How their movements change when they have to carry something with them? Think about the problem yourself. How have you adapted your movements to go down a spiral staircase? In any case, someone inside you can take care of the performance. You just do not know how controlling movements is done. Similarly, it is hard to know what kind of information processes are needed in a variety of thinking demanding problem situations.

Although human thinking is not fully explicit and conscious, it is possible to study what happens in the human mind, when people think (Ericsson and Simon 1984, Myllylä and Saariluoma 2022, Saariluoma 1995). Human behavior and especially human speech are expressions of human thinking. They enable researchers to understand what people think and why they think the way they do. Such analysis of mental content has long been common in professional and clinical psychology (Beck 1976, Ericsson and Simon 1984, Newell and Simon 1972). This research has revealed some important structural elements in human information processing.

People use their experiences to build different patterns of information such as concepts and mental models in their long-term memory (Johnson-Laird 2008, Lawrence and Margolis 1999, Neisser 1976). Concepts can be seen as memory representations of people, objects, things, and events. Mental models are complex structures that represent people, objects things and events (Johnson-Laird 1983, 2008). The latter are usually constructs of the former. Understanding what people think means understanding the information content of mental representations, mental contents or simply contents of thoughts.

The thinking of experts is exceptional compared to novices. Because they have a more extensive and more relevant set of mental models, they are better able than beginners to represent problem situations in an appropriate way. Experts are able to encode relevant issues that novices easily pay less attention to. The

superior performance of experts is possible because their years of training allow them to have a broader and more relevant storage of domain specific knowledge (Ericsson 2006).

Qualitative research methods such as interviews, surveys, protocol analysis or focus groups allow researchers to gain insight into the contents of subjects' thinking and thus describe how and what people think about the problem situations they encounter (Duncker 1945, Ericsson and Simon 1984, Krippendorf 2018).

Ultimately, intelligent technologies should do the same things that humans have done so far. It is possible that intelligent artifacts will perform their tasks faster and more tirelessly manner. It is possible that they will process information differently from humans, but the most important criterion is that new technologies will be able to do what humans have done so far. The concept of multiple realizability is fundamental in this context (Bickle 2020).

## **Multiple Realizability**

Multiple realizability is a fundamental concept for understanding how machines can perform human tasks that traditionally require intelligence (Bickle 2020). It simply means that the same information process can be performed by different hardware. Humans can perform elementary arithmetic calculations, but so can abacuses or calculators. Thus, the same information process can be implemented in many ways by means of different hardware and software.

People can do basic arithmetic in their heads, but they can also do it with an abacus. Pocket calculators can perform the calculation automatically, given an input. More intelligent systems may in the future perform complex calculations to serve some conceptual or practical goal with very little human involvement.

Multiple realizability means that information processes can be independent of the processing system. Information processes have their own ontological status, and we need specific theoretical concepts to analyze and study them in cognitive science. The independence of material processing systems allows the construction of different physical information processing systems to perform the same information processing tasks. Ontologically, it is therefore impossible to attach information processes to any single processing system. Computers can have different programs that change their behavior independently of the hardware. The same hardware can execute an infinite number of programs. Therefore, algorithm science is related to, but distinct from, computer electronics.

The hardware provides the necessary platform for the software. Similarly, the human brain is plastic, and the brain can therefore implement different types of mental contents. For example, people can speak different languages depending on their linguistic environment. The brain hardware does not explain how speakers of different languages express the same ideas, but this explanation must be sought in the linguistic environment.

Multiple realizability opens new possibilities for designers. They can extract an information process from one environment and implement it with another physical tool. Multiple realizability allows human thought processes to be implemented on computers, if only we understand what the source process is. The design framework for these design methods that move from human thinking to machine processing is cognitive mimetic design method.

## **Cognitive Mimetics**

Mimetic design has been a standard tool in design thinking for decades (Bhusan 2009). It refers to technology design, where designers mimic an existing phenomenon or system to generate new technological solutions. Sources for designs are often objects and their structures, in nature. Design mimetics has often focused on the structural and physical similarity between natural entities and technical artefacts. Common examples are aircraft mimicking birds or Velcro tape mimicking burdocks.

Mimetics where the source is a biological system, or phenomena is called biomimetics (Bhusan 2009). This remains the mainstream of mimetic design thinking. However, instead of mimicking physical structures and

processes, i.e. matter and its form or energy, mimetics can also be based on mimicking information processes (Karvonen et. al. 2003, Saariluoma et.al. 2018).

The structural and physical similarity of source and idea is not necessarily the only form of mimicking. There are categories of design problems, that are not structural or physical, but are related to information processing. Robotics and artificial intelligence (AI) provide two main examples. In design fields related to human thinking, designers can still find new ideas by exploring possible solutions by mimicking human information processing and thinking. When the source is an information process, such as thinking, we can talk about cognitive mimetic.

The purpose of cognitive mimetic is to use existing information processes to facilitate the construction of new technical solutions. The focus is on using human mental processes as models to generate new design ideas for intelligent technologies. This approach is natural as designers seek to free humans from performing intelligent tasks in industry and replace human labor with intelligent machines.

A naïve but intuitive example might make our strategy understandable. Consider the way in which design mimetics could be used to design a cyborg table tennis player. The first problem is to create hands that play table tennis. They need to be similar to human hands in terms of to size and elasticity of movement. They would have to have the right pressure, timing, and tempo to play like Jan-Ove Waldner (one of the best table tennis players of all time). The motion control of cyborg robots should be able to mimic the sensory-motor processes of experts. It should also be able to analyze game situations with human-like intelligence, and machine learning could be used to improve cyborg performance (Williams 2024).

The critical question here is whether human hand imitation and eye-hand coordination processes are sufficient to express all the human skills involved in playing table tennis. Skilled players often use their hands routinely when playing, but they also must solve unique and complex problems. They must rely on thought processes such as categorization, inference, decision making, problem solving, and constructive thinking to create new visions.

Expert players in any game, whether chess or table tennis, develop a “feel” for the situation which is more than any numerical attribute that may be computed from the brute facts of the situation (Dreyfus 1992). Rather it is this situational picture which gives the facts a meaning in terms of human goals. Thus, experts must rely on thought processes such as categorization, inference, decision making, problem solving, and constructive thinking as well as vast and contextually appropriate knowledge to make sense and act skillfully in changing circumstances. Even the most careful and complete capture of pure behavior tells relatively little of either the game or of human intelligence, and therefore our example implies a further step is required to develop truly intelligent machines that integrate with human intelligence in a natural way. In terms of the source, this is the main goal of understanding in cognitive mimetics. As noted, given the multi-leveled nature of human cognition and its’ variant and invariant features, this task is not easy, but it is possible and just like any other task, becomes easier once expertise and general practice develops.

Multiple realizability does not mean that two systems have to process information in the same way in order to achieve the same result. Airplanes do not fly in exactly the same way as birds. Multiple realization has therefore its pragmatic in orientation. Nevertheless, the key problem for deriving value from the mimetic process is how the findings can be operationalized in the computational context of machines on the one hand, or in the HTI issues in joint cognitive systems design. But they obey the same laws of aerodynamics. In design, the relationship between the source and target processes need not be identical.

## **Human digital twins - Modelling information processes and thoughts**

Understanding the relationship between source and design processes is often based on modeling. In cognitive mimetics it is also logical to use computational and other models to explicate, clarify and to modify designers’ thoughts. If the models used to assist designers work are digital, they are usually referred to as digital twins.

Digital twins are computational models of industrial objects. They have become important elements in design thinking. They can be used to model and design complex systems. Digital twins model physical objects in industry, such as turbines, power stations, control systems or paper machines. But they are also used to assess how people interact with industrial processes. For example, much of modern aircraft design is based on digital twin models.

People will continue to be an integral part of technological systems in the future. People are not just users of technologies; they are also the objects of technical systems. Therefore, modelling of technologies should not be limited to technical artefacts, but should also take into account the different thoughts, roles and actions emerging when people use artefacts. When digital twins include human beings and their information processes in their different roles, the models can be called human digital twins (HDTs) (Saariluoma, Cañas and Karvonen 2022). As many industrial accidents result from poorly designed interaction environments (Reason 1990), it makes sense to use digital modelling to design human interaction with the artefacts. However, it is not at all clear how to use digital twins to provide meaningful information about people. Basic models may involve the use of controls and feedback systems. In addition, advanced systems should also provide information on how effectively people can use the systems and how they are organized to use the technologies. How to design the controls so they are easy and pleasant to use?

Human digital twins can be used to analyze how people perform intelligent tasks. Detailed descriptions of the mental contents and processes involved in the use of technologies facilitate the design of requirements for human-technology interaction. HDTs should model not only how artefacts work, but also how people use them. One approach to building HDT models is the cognitive mimetic approach. By means of mimetic methods it is possible to use contextually relevant human information processes to build intelligent systems.

Mimetic design involves using a source in the natural or artificial world to inspire technological solutions. Cognitive mimetics explores the common and individual human cognitive processes, and the relevant mental contents, representations, and constraints that impose limits and forms on these processes in a designed industrial process.

The result of cognitive mimetic analysis of human actions and performances and can be used to build HDT models. Perhaps the first example of cognitive mimicking and human information processing was Turing's model of the thinking mathematician, the Turing machine (1936-7). He did not focus on the biological structures of humans (unlike biomimetic), but on their information processing. Some years later, Herbert Simon and colleagues began to empirically study human cognitive processes, thus extending mimetic thinking from introspective to objective or behavioral analysis (Newell and Simon 1972). Applying cognitive mimetics thinking to modeling HDT requires explaining how (and why) people act the way they do, what difficulties they have, and how they experience using technologies. Thus, cognitive analysis enables the incorporation of the most important aspects of the use of all technological artefacts into HDT models.

Human digital twins play multiple roles in industrial design processes. They can be used to explicate and illustrate design ideas, as well as to explore different versions of a design object. They can also be used to design training processes and to train employees. Thus, human digital twins can be used in the same way as other digital twins in industrial design, with the difference that they aim to improve human-technology interaction and human work processes. The latter need not be limited to work performance, but there is nothing prevent the use of human digital twins for the study and design of ethical and values processes. values being as much the result of human thinking as actual cognitive work processes.

## **Designing Ethical Thinking**

Ethics is an interesting challenge when developing intelligent technologies by means of mimicking human thinking. At the earliest stage, designing what should be done may mean guidelines for good work practices. HDTs can, however, also be used to develop ethical principles for design (Saariluoma, Cañas and Karvonen 2020).

A theoretically important problem is whether big data can be used to derive values for design. It seems promising to use intelligent technologies to answer to questions about what should or should not be done. But the interesting question is whether values can be derived from existing data sets. In ethical theory, it has been commonly argued that values cannot be derived from facts. The problem is called is-ought-to problem or Hume's guillotine (Pigden 2010).

According to David Hume (1972), values cannot be derived from facts, just as the emotions that drive action cannot be derived from reasons. Since intelligent systems are processors of facts, one may ask whether ethical machines might be possible. However, ethics is a real-life process. People analyze actions and situations emotionally and cognitively (Saariluoma 2021, Saariluoma, Canas and Leikas 2016). In doing so, they learn

rules, such as “this situation feels good/bad.” Cognitive analysis of actions is linked to emotional analysis. The combination of action, emotional state and the associated cognitive representation can be called the primary ethical schema. Through processing ethical information where emotions and cognitions interact in social discourse, primary ethical schemas are refined into ethical norms. In ethical reasoning, through the analysis of actions and their outcomes, people can construct rules about what kinds of actions lead to unpleasant or unacceptable ethical outcomes.

Ethics does not exist without combined emotional and cognitive processing. Hume’s guillotine erroneously dismantles the primary ethical circle and separates emotions (or passions) from cognitions (reasons) in the ethical processing of information. Ethical information processes or ethical thinking involve intelligent systems that can construct proposals for ethical rules, principles and practices. Resolving Hume’s guillotine thus opens up new ways to develop stronger forms of ethical AI and ethics (Saariluoma 2021; Saariluoma and Leikas 2020).

To unlock the logic of ethical cycles, it is useful to take an illuminating example that is familiar to all. In the thirties, public relations or propaganda experts worked to increase smoking among the population, and to achieve their goal they wanted to override the social norm that women should not smoke, thus claiming that smoking liberates women from patriarchal constraints. Women who smoked were free to enjoy life equally to men.

However, in the late fifties and early sixties, a link was found between smoking and lung cancer and many other diseases. Because the diseases are lethal and painful, people no longer saw smoking as a positive behavior, but as a negative one. As a result, cigarette advertising was banned, and class actions became possible in the courts. Ethics changed because the negative consequences of this human activity were recognized. The example presented shows how practical life overrides Hume’s guillotine (Saariluoma 2021).

## **Human and machine thinking in designing intelligent systems**

Although intelligent machines have long been associated with human thinking (Turing 2009), the relationship between human and machine thinking remains difficult to define precisely (Dreyfus 1992, Simon 2019). This issue was important at the end of the last century, but today the focus of AI and robotics has shifted to practical applications, and therefore the problem may seem less fashionable.

The problem of analytical comparison between machine and human thinking started with the initiative Turing (2009). He argued, in a behaviorist but illogical way, that if one cannot distinguish how machines solve tasks that require intelligence from how humans can solve them, one can say that machines think like humans. The schema was called the Turing’s (2009) test. Turing’s test is problematic because it assumed that the similarity of system executions means that processing is similar (Saariluoma and Rauterberg 2016).

A fundamental difference between human and machine intelligence is the ability of humans to process relevant information. Relevance, or the ability to say why some things belong together, is beyond the reach of any mathematical system for the reason that there is no mathematical basis for saying which members of a set belong to the same subset (Saariluoma and Rauterberg 2016). Thus, it is necessary to make a classification into relevant and irrelevant on the basis of additional non-formal knowledge. Since logically valid inferences are not necessarily meaningful, formal theoretical languages are not sufficient to describe human thinking (Saariluoma and Karvonen 2023).

Intelligent machines rely on theoretical languages to process information. In particular, the limitations of the three theoretical languages, formal, computational, and natural, allow us to look at the classical problem of comparing human and machine languages from a new perspective. Machines can process information, but their limits depend on the limits of the representational language on which they rely. Machines can only be as intelligent as the limits of their representational language allow. All intelligent machines use computational languages to represent information. Thus, the limits of the computational languages determine the limits of the machines' intelligence. If a computational language does not have the ability to express or construct representations, then machines operating according to that language will not have that ability either. Thus, the differences between natural languages and computational languages provide an interesting basis on which to discuss human and machine intelligence and their relative reasoning abilities. One crucial limitation of computational languages is their fixed semantics. The world can change indefinitely, and therefore natural

languages have dynamic semantics. References in natural languages are locally associated with symbols and ideas that convey meanings. The meanings of computational languages are defined by references as the alphabets and operations of these languages are constructed. In principle, computational representations can be used to describe any part of the real world. However, they are always finite. The world, i.e. objects, events, actions, and ideas, are not finite, but can be infinitely complex. Even an object as simple as a teacup has infinite properties. Thus, no AI system can produce infinite representations of the world, just as no description of an infinite world can contain itself.

Computational languages and their representations are thus always finite representations of the world, and a universal and general machine intelligence is therefore not possible. Whenever the meaning of a term or operation is established, some part of the world is excluded from the system. However, the problem of human and machine intelligence can be viewed from another perspective. Artificial intelligence systems, such as chess-playing programs, may exceed human performance, but they are useless in other areas. Similarly, it is possible to create computational languages and their computational representations for other domains. Due to the fixed semantics of these languages, their generalizability is limited, and the smooth context switching typical of human reasoning is difficult or even impossible to achieve. Moreover, fixed semantics also means that AI prefers fixed domains or environments - for obvious reasons. Human natural languages work differently, as they have an infinite number of symbols and can create and define new symbols for any given situation. Whereas computational languages derive their semantics from definition and conventions, natural languages derive their semantics from concepts and people's ideas, and for this reason these semantics are inherently dynamic. In fact, computational terms derive their meaning from natural languages, and their representations are subsets of the representations of natural languages. Due to the dynamic nature of human thought, natural language expressions derive their content from the human mind and thus have no predefined limits. It is of course true that computational (and formal) languages also derive their content (and other properties) from human thought. However, the relationship is very different, since natural language is part of the same immediate system as thought, and is therefore, by necessity and evolution, highly related and complementary. In external and artificial systems using computational languages, this proximity has been lost and various constraints have been introduced.

## Discussion

The fixed semantics of computational languages and their associated representations make it impossible for AI to achieve the generality or versatility of human reasoning. Moreover, AI currently has no other basis in formal and computational languages. It is, of course, possible to build domain-specific and problem-specific systems that can transcend human thinking on those problems. Nevertheless, since there is no limit to the number of problems that AI should solve, it is not reasonable to argue that AI as a whole can outperform human performance in all known specific areas. In such cases, it can be said that AI is "good enough" but not efficient enough to outperform human performance in all its general forms and manifestations.

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