

Metascience of Content-Based Cognitive Ergonomics

Pertti Saariluoma¹, Mari Myllylä¹, and Jose Juan Cañas²

¹University of Jyväskylä, Faculty of Information Technology, P.O. Box 35 (Agora), FI-40014 University of Jyväskylä, Finland

²University of Granada, Campus Universitario de Cartuja C. P. 18071, Granada, Spain

ABSTRACT

In the ongoing technological revolution from 4.0 to 5.0 life, a critical issue is cognitive ergonomics for intelligent information processing. Joint Cognitive Systems (JCS) is a helpful concept to understand the strengths and limitations of human and machine information processing and reasoning. To operate in the real world, the JCS must represent the relevant actions, agents, goals, and context. However, machine representations such as Turing machines or formal automata represent the world in terms of meaningless symbols. Such formal machines must be interpreted, i.e., their representational elements and operations that generatively manipulate representations must be given meanings, which is often called symbol grounding or interpretation. The representational elements must be given meanings, otherwise they cannot function in a meaningful way in the real world. It seems that information content and its relevance are a consequence of human information processing and thinking. An interpreted Turing machine has a set of domain-specific rules or operations that manipulate symbolic states from one to another. Information content makes it possible to ask and answer new kinds of questions, for example about truth and validity. Information content and its relevance thus form the human part of intelligent JCS. The problem of information content, its relevance and truth form the standpoint of a new kind of ergonomic thinking. It focuses on the content of relevant information. This field of ergonomics can be called content-based, because the topic of its analysis as well as its arguments are based on the content of information processes in human-machine interaction.

Keywords: Cognitive ergonomics, Joint cognitive systems, Human-technology interaction, Information contents

INTRODUCTION

Ergonomics is a field of scientific research that examines the factors that influence human-technology interaction. These factors can be cultural, organizational, physiological, or cognitive (Bridger, 2009). Interaction depends not only on how we see people, but it is also important to pay attention to the nature of technologies. Today, when artificial intelligence (AI) and intelligent technological solutions are the central enigma of technological development, it makes sense to ask what the technological revolution means for cognitive ergonomics.

Intelligent machines can perform tasks that previously could only be done by humans. Humans are already delegating many tasks requiring intelligence

to machines or actively collaborating with intelligent technical artifacts in group work. Intelligent technologies, such as AI systems, are being adopted at an ever-increasing rate in various industries and businesses, as well as in everyday professional and personal use (Eurostat, 2026; World Economic Forum, 2025). As a result, the changes in technologies are leading to profound changes in work processes. Accordingly, future ergonomics should find means to cope with the new type of human-technology interaction processes.

Intelligent machines are intelligent because they can process information and perform tasks that require human intelligence and thinking. From the beginning, Turing saw the intimate connections between human thought and computing machines. Why not? Turing machines were models of thinking mathematicians (Petzold, 2008; Turing, 2004/1936, 1950). Consequently, new ergonomics must conceptualize new intelligent aspects and ways of human-technology interaction processes.

In intelligent human-machine systems, humans and machines “collaborate” to perform a task. Such collaborative human-machine systems have been termed “joint cognitive systems” (JCS) (Woods and Hollnagel, 2006). JCS can be understood as both an engineering approach and an object of design. In JCS, agents such as humans and AI work together through controlled actions and co-agency toward common goals (Woods and Hollnagel, 2006) to maintain control and counteract the effects of perturbations in changing situations (Hollnagel, 2002). For example, new cars are equipped with numerous automatic assistance systems, such as lane departure warnings, parking meters, and distance control systems, which together with the human driver form a collaborative functional unit for co-driving a car (Hollnagel, 2002; Xu and Gao, 2024). Therefore, the outcomes of this collaborative task need to be considered from the point of view of the collaboration between the agents and the common responsibilities of the agents.

Automation and autonomy of technology, human-machine interaction, and JCSs in which the actions of agents depend on the actions of other agents may introduce new types of features, demands, requirements, and risks that must be considered in the design of technology, work processes, and training for their use (Cañas, 2022; Hollnagel, 2002). In JCSs, humans and machines can be understood as interacting elements and sources of performance diversity within an overall system (Hollnagel, 2002). Understanding interactions within JCSs requires knowledge of human perception, thinking, action, and the cognitive and non-cognitive components of mental information processing, such as motivations and emotions, that can influence human behaviour (Cañas, 2022; Hollnagel, 2002).

One must ask what it means to shift the focus of ergonomic thinking from traditional capacity-based thinking to information content, and to use content-based arguments in solving interaction problems. Since the arguments are based on the properties of mental content, such ergonomics can be called content-based (Saariluoma, 2022; Saariluoma, Cañas and Myllylä, 2024). Analysis and design processes in content-based cognitive ergonomics are based on the properties of the information content involved. As a paradigmatic approach, it provides tools to construct AI and intelligence-based technological solutions.

Intelligent agents and technologies have become so successful at processing information and solving problems that they may appear to possess some level of human-like reasoning. This may also lead to an anthropomorphic assumption that artificial agents are thoughtful and have mental states, or that they have achieved human-level thinking, when in fact they may be limited to their programming or data and lack the ability to solve novel problems (Ghiglino and Wykowska, 2020; Proudfoot and Copeland, 2012). However, human thinking has its specific features and strategies that make it possible for people to be flexible and adapt to complex interactions with the world and other people (Ghiglino and Wykowska, 2020; Müller, 2020). People are also able to question and reflect on rules, norms, rationales, and the content of their own or others' thinking (Müller, 2020; Saariluoma, 1997). Thoughts have content with meanings—they are about something that has phenomenally experienced qualities that have a “reference to reality that goes beyond pure syntax or formal semantics” (Müller, 2020, p. 12). Thus, current AI lacks human-like mental flexibility and semantic understanding, which are important for efficient human-machine collaboration (Cañas, 2022; Minsky, 1968; Newell and Simon, 1972).

Nevertheless, the problem of how machines think and cooperate with humans is real today, as humans are massively adopting technological solutions to be used in various practical tasks. Work and daily life processes have so far been managed and controlled by people, but in the near future, the same processes will be realized by intelligent machines. To accomplish this transformation, it is important to develop machines that think like humans. The first steps towards the future of intelligent technologies were taken by Alan Turing (2004/1936, 1950) and Konrad Zuse (Alex et al, 2000).

Turing's Vision on Thinking Mind

Turing machines (2004/1936, 1950) are symbol-manipulating systems. Like mathematicians, a Turing machine starts from a set of symbols, which could be called alphabets: They can be natural numbers, for example, or any set of discernible symbols. These symbols can be combined into words, which are sets of alphabetic symbols. Symbols stand for something outside themselves. The same basic ideas and conceptual constructions have been used in the formal theory of automata (Salomaa, 1985). Symbols (or words) are combined into representations (Salomaa, 1985).

A Turing machine also has a set of domain-specific rules or operations that manipulate symbolic states from one to another (Newell and Simon, 1972). Consequently, Turing (1936) machines can to some extent process information like thinking humans. At least they can perform tasks that require intelligence.

Since modern intelligent computing devices are essentially Turing machines or automata, the challenge for cognitive ergonomics is how to understand and design human-intelligent machine interaction processes. Clearly, some fundamental renovations of traditional ergonomics are required. The basic thesis of this paper is to show that the new type of cognitive ergonomics could be built on the analysis of mental content, and this field can be called

content-based cognitive ergonomics (Saariluoma, 2022; Saariluoma, Cañas and Myllylä, 2024).

Human and Machine Thinking

The ability of machines to think, in a sense, makes it possible to use them in tasks that require intelligent information processing. The critical question is what the similarities and differences between human and machine thinking are. From this point of view, more than half a century of comparative conceptual analysis is illuminating with respect to the problems of designing and constructing intelligent technological applications.

Holyoak and Morrison (2012, p. 2) define thinking as “the systematic transformation of mental representations of knowledge to characterize actual or possible states of the world, often in service of goals” (see also Newell and Simon, 1972). Thinking, which can be conceptualized as information processing in which new information is derived from existing information to postulate inferences (Chater, Heit and Oaksford, 2009; Oaksford, Chater and Steward, 2012), is often organized around representational information content structured in mental models (Johnson-Laird, 2006; Neisser, 1976) or patterns (Chase and Simon, 1973; Myllylä and Saariluoma 2022; Rumelhart and Ortony, 1977/2017; Saariluoma 1995). Thinking can be studied from several different perspectives, such as reasoning, judgment and decision making, problem solving, remembering, wishing, dreaming, and automatic thinking, where thinking is about something (Chater, Heit and Oaksford, 2009; Halpern, 2013; Holyoak and Morrison, 2012). Human thinking is often apparent in a conscious form of reasoning, but it can also be related to many subconscious and lower-level mental activities (Chater, Heit and Oaksford, 2009; Holyoak and Morrison; 2012). Unfortunately, human cognition is not always rational, and thinking can be erroneous (Bailey, 2008; Holyoak and Morrison, 2005; Kahnemann, 2011). For example, there may be incorrect mental processes or representations that lead to cognitive illusions (Pohl, 2017), cognitive or emotional biases (Kahneman, 2011), or argumentation fallacies (Van Eemeren and Grootendorst, 2004). The resulting irrational behaviour can be “rigid and reactive, especially cognition oriented towards learned rather than learning behaviour, and based on belief rather than evidence”, with “outdated non-contextual information containing unexamined cognitive inaccuracies” (Bailey, 2008, p. 66).

In the discussion of how computers can simulate and implement human cognitive processes such as thinking, there are two central concepts: weak AI and strong AI. The former sees the computer as a powerful tool for studying the mind, testing psychological explanations, and simulating human intelligence, while the latter sees the brain as a computer and the machine computer as having the potential to become a mind with mental abilities and characteristics such as cognitive states, if appropriately programmed (Müller, 2020; Searle, 1980).

The best-known representatives of weak or instrumental AI are probably John Searle (1980), Hubert Dreyfus (1992), and Roger Penrose (1990). They have all looked at Turing’s (1950) problem of can machines think from

somewhat different positions. Searle (1980, 1990) argued that mechanical rule-following is not thinking, Dreyfus (1992) pointed out that machines cannot know what is relevant, and Penrose (1990) that human conscious mind goes beyond mechanical computation.

In the problem of designing AI and intelligent technologies, the problem of weak and strong AI plays a role. Assuming that absolute positions would be true, strong AI would imply that we could exhaustively mimic human thinking by intelligent machines, and thus design intelligent technologies for any imaginable purpose. Assuming that weak AI people are right, one should ask where the limits of designing intelligent technologies are. It would mean that humans can be replaced in some aspects of information processes, but not in all possible cases and aspects.

Assuming that strong AI or AGI (artificial general intelligence) would be possible, no aspect of human intelligence would need to be formulated outside of AI systems. A single AGI system would handle all possible intelligent information processing tasks. Conversely, humans will need to add some aspect of their information processing skills to collaborate with intelligent applications.

On the Limits of Turing's Thinking

A critical process from an AGI perspective in Turing's (2004/1936, 1950) model of human reasoning is the definition of the meanings of symbols used in representation and the formulation of transformation rules that manipulate representations (Newell and Simon, 1972). This problem has been called meaning-giving or symbol grounding (Harnad, 1990; Wittgenstein, 1953). The critical question is how the machine representation relates to the actual world.

For human subjective knowledge of the real world, the meanings of things and the connections of semantic representations of signs with some aspects of reality are acquired and constructed throughout life through phenomenal experiences and thinking (Holyoak and Morrison, 2005; Müller, 2020). No AI machine can act rationally and sensibly if the semantics of symbols and forms of operations do not make sense. Even for neural networks and Large Language Models (LLMs) it is necessary to construct a reference relationship between symbols and the actual world. Their sense-making information processing is possible because the data they use contain tacitly human structured and collected information.

In Turing's (2004/1936) machines, or any formal, logical or mathematical, representations, the semantics of elementary symbols is based on reference to mathematical sets, often called model sets (Hintikka, 1973). Operations manipulate symbolic expressions into other expressions that should make sense in given model sets. The basic formal nature of Turing's (2004/1936) model leaves many steps in connecting the computational models to the actual world intuitive, and this issue has proven very difficult in our attempts to understand the foundations of AI and intelligent technologies.

Turing (1950) thought the processes of connecting formal models with the actual world quite simple. Symbols can have any kind of reference to the real world. Symbols can represent Chinese characters as any states of affairs in the actual world (Proudfoot and Copeland, 2012; Searle; 1980; Turing,

2004/1936). However, assigning real-world meanings to symbols is not trivial or automatic, but an essential part of human thinking and intelligence (Pezold, 2008; Saariluoma and Karvonen, 2024). Thus, interestingly and logically, the problem of giving meaning has important consequences in discussions about the relationship between machine information processing and human thinking.

The problematic character of meaning giving to connect machine intelligence with actual word descriptions of Turing's AI thinking was first observed by Ludwig Wittgenstein (1953). He himself had developed a formal logic-based "picture" theory of representation in *Tractatus* (Wittgenstein, 1961/1921). In developing his theory of syntax-based representation, however, he had already seen the importance of providing means for terms or symbols (Wittgenstein, 1961/1921). However, it was only after his return to Cambridge in 1929 that he began to think about the problem of word meanings, and, as is well known, he spent the rest of his life working on this problem without really being satisfied with any of his models for defining word meanings.

Since Wittgenstein's (1961/1921, 1953) initial work, the problem of meaning giving in the design and construction of intelligent technologies has attracted attention in various discourses that have their roots in the problem of giving meaning or symbol grounding (Harnard, 1990). One of the branches of the comparison between machine and human thinking is the dispute between strong and weak AI (see, e.g., Müller, 2020; Proudfoot and Copeland, 2012).

CONTENT-BASED COGNITIVE ERGONOMICS

Ergonomics studies human technology interaction. In constructing intelligent systems to replace humans in thought-related tasks, information content in machines and mental content in the mind become topical issues. It is essential to study how human intelligent technology processes are constructed, and in this work, mental contents and meaning giving are critical issues.

In content-based thinking, mental contents are taken as representational information contents, and the analysed properties of these contents are used to explain human actions (Myllylä and Saariluoma, 2022; Saariluoma, 1995, 1997). The analysis and design of content-based information processes is essential to the development of intelligent technology applications such as JCSs.

Focusing on mental content allows new types of questions to be asked and answered. For example, one can discuss the truth and validity of representations: while engineers in a nuclear power plant may not be aware that the system is entering a critical state, the question is not about their processing capacity, but about the validity of the information content in their mental representations. If one has not explicated the mental contents in human thinking and information contents, it does not make sense to ask whether their representations are correct (Saariluoma, Cañas and Myllylä, 2024).

Contents are also necessary to understand whether people use technical tools correctly. It may be difficult to see the function of mental content in ergonomics, because the space of necessary scientific knowledge seems to be sufficient. However, in terms of mental content, many classical concepts can

be examined from a new perspective. For example, “reliability” can refer to a system that works as it should, i.e. the system is fault-tolerant (Saariluoma, Cañas and Myllylä, 2024). A simple example comes from user interface (UI) design. If the user does not understand the meaning of the data presented in the UI of an AI-assisted system, e.g. because the user does not have the necessary knowledge to make sense of the data and correctly interpret what the data means, or because the information content provided in the UI does not match the assumed state of reality for the user, the user may no longer want to use the system as the designer intended or may no longer trust it (Myllylä, Karvonen, and Koskinen, 2024). This example illustrates both a practical usability problem and a phenomenon that requires a deeper application of content-based cognitive ergonomics to solve. In JCSs, where the work between humans and artificial agents is highly interdependent, it is necessary that different agents understand each other’s meanings and actions. This implies not only that the human can understand what the artificial agent is doing, but that the artificial agent must also be able to pay attention to and correctly interpret the intended meanings and actions of the human, and to adapt to their changing mental states, actions, and situations (Cañas, 2022). In any case, adaptive systems have their domains of relevance, and no system can adapt to all imaginable environments.

Intelligent systems are based on mathematical and formal structures, but in actual worlds they should operate with content. Therefore, they need to be given interpretations so that they can operate in a sensible way in real world tasks. Autonomous ticketing for airplanes cannot be used to control how cars should drive, although both have the same structure as a formal automaton [i.e., $A = (Q, \Sigma, \delta, q, F)$, where Q = finite set of data, Σ , set of inputs, δ = transition function, q = initial state, and F = set of final states]. Interpretations require the construction of sense-making semantics for symbolic representations and relevant representational content and processes to operate them in a meaningful way.

In ergonomics, it is essential to ground solution models in science. For example, the limited information processing capacity of humans has been used to solve many technical problems related to usability (Nielsen, 1993; Wickens and Carswell, 2012). However, on this ground it is not possible to obtain an exhaustive basis for solving problems of designing intelligent technological applications.

Meaning giving is a critical process in content-based ergonomics. Designers should investigate how people construct meanings in their current work and how these meanings can be used in working with future intelligent solutions. Meaning and its definition is a tool for future designers in content-based cognitive ergonomics.

Work processes and activities will be based on joint cognitive systems in which human intelligence is extensively supported by intelligent artifacts and AI. The society in which unified information processing systems are implemented is called the Cognitive Society or Society 5.0. An important tool in the development of new forms of social life is content-based cognitive ergonomics.

CONCLUSION

Human action in social life has always been guided by human thinking. Human thought processes can be imitated by intelligent technologies. However, before it is possible to imitate human-driven information processes by machines or to develop new types of actions, it is necessary to know what the existing processes are like. In this way, human thinking can provide patterns for designers of a new cognitive society.

The world is infinitely complex, so a universally valid semantics would have to have an infinite number of symbols, and relevant operations could be constructed in an infinite number of ways. Thus, content-based information processing has no limits in solving individual instrumental processing problems, but it is impossible to find AGI and strong AI solutions. From the point of view of ergonomics, content-based cognitive ergonomics is required in the construction of any instrumental intelligent technological solution or joint cognitive system. The main task of content-based cognitive ergonomics is to construct meaning giving interpretations and representational contents for instrumental joint cognitive systems.

ACKNOWLEDGMENT

We would like to thank the University of Jyväskylä, Faculty of Information Technology, for supporting Mari Myllylä with a researcher mobility grant for the research collaboration at the University of Granada and for the preparation of this manuscript. The research by Pertti Saariluoma and Mari Myllylä was part of the HiFive-project funded by Business Finland (project number 5785/31/2023).

REFERENCES

- Alex, J., Flessner, H., Mons, W., Pauli, K. and Zuize, H. (2000). *Konrad Zuse: der Vater des Computers*. Parzeller.
- Bailey, C. E. (2008). "Semantically mediated integration of cognition in homo sapiens: Evolution, grammar, uncertainty, and cognitive accuracy", in: *Cognitive Science Compendium* (vol. 2), Sun, Miao-Kun (Ed.). pp. 65–107. New York: Nova Science Publishers, Incorporated.
- Bridger, R. S. (2009). *Introduction to ergonomics*. Boca Raton: CRC press.
- Cañas, J.J. (2022). AI and ethics when human beings collaborate with AI agents, *Frontiers of Psychology*, 13, 836650. <https://doi.org/10.3389/fpsyg.2022.836650>
- Chase, W. G., & Simon, H. A. (1973). Perception in chess, *Cognitive Psychology*, 4(1), 55–81. [https://doi.org/10.1016/0010-0285\(73\)90004-2](https://doi.org/10.1016/0010-0285(73)90004-2).
- Chater, N., Heit, E. and Oaksford, M. (2005). "Reasoning", in: *Handbook of Cognition*, Koen Lamberts and Robert L. Goldstone (Eds.). pp. 298–321. London: SAGE Publications Ltd
- Dreyfus, Hubert L. (1992). *What computers still can't do: A critique of artificial reason*. Cambridge, MA: MIT press.
- Eurostat (2026). *The use of artificial intelligence technologies in the European Union – Key results – 2026 edition*. Statistical reports 26 March 2026. Luxembourg: Publications Office of the European Union. <https://doi/10.2785/9221093>

- Ghiglini, D. and Wykowska, A. (2020). "When robots (pretend to) think", in: *Artificial intelligence: Reflections in philosophy, theology, and the social sciences*, Benedikt Paul Goecke, and Astrid Marieke Rosenthal-von der Pütten. (Eds.). pp. 49–74. Paderborn Brill | mentis.
- Halpern, D. F. (2013). *Thought and knowledge: An introduction to critical thinking*. New York: Routledge.
- Harnad, S. (1990). The symbol grounding problem, *Physica D: Nonlinear Phenomena*, 42(1-3), 335–346.
- Hintikka, J. (1973). *Logic, language-games and information*. Oxford: Clarendon Press.
- Hollnagel, E. (2002). Cognition as control: A pragmatic approach to the modelling of joint cognitive systems, *IEEE Journal of Systems, Man and Cybernetics*, 10, 1–25.
- Holyoak, K. J., and Morrison, R. G. (2005). "Thinking and reasoning: A reader's guide", in: *The Cambridge Handbook of Cognitive Science*, Keith Frankish and William Ramsey (Eds.). pp. 1–12. Cambridge: Cambridge University Press
- Johnson-Laird, P. N. (2006). *How we reason*. Oxford University Press.
- Kahneman, D. (2011). *Thinking, fast and slow*. Penguin Books.
- Minsky, M. (1968). *Semantic information processing*. Cambridge: MIT press.
- Myllylä, M. T., and Saariluoma, P. (2022). Expertise and becoming conscious of something, *New Ideas in Psychology*, 64, 100916. <https://doi.org/10.1016/j.newideapsych.2021.100916>
- Müller, T. (2020). "Conscious, thinking, and intelligent machines? Some clarifying remarks in the field of artificial intelligence", in: *Artificial intelligence: Reflections in philosophy, theology, and the social sciences*, Benedikt Paul Goecke, and Astrid Marieke Rosenthal-von der Pütten. (Eds.). pp. 3–14. Paderborn Brill | mentis.
- Neisser, U. (1976). *Cognition and reality: Principles and implications of cognitive psychology*. San Francisco, CA: Freeman.
- Newell, A., and Simon, H. A. (1972). *Human problem solving*. Englewood Cliffs (NJ): Prentice-Hall.
- Nielsen, J. (1993). *Usability engineering*. Boston, MA: Academic Press, cop.
- Oaksford, M., Chater, N., and Steward, N. (2012). "Reasoning and decision making", in: *The Cambridge Handbook of Cognitive Science*, Keith Frankish and William Ramsey (Eds.). pp. 131–150. Cambridge, MA: Cambridge University Press.
- Penrose, R. (1990). Précis of the emperor's new mind: Concerning computers, minds, and the laws of physics, *Behavioral and Brain Sciences*, 13(4), 643–655.
- Petzold, C. (2008). *The annotated Turing: A guided tour through Alan Turing's historic paper on computability and the Turing machine*. Indianapolis, IN: Wiley Publishing.
- Pohl, R. F. 2017. "Cognitive Illusions", in: *Cognitive Illusions: Intriguing Phenomena in Thinking, Judgment and Memory* (2nd ed.), R. F. Pohl (Ed.). pp. 3–22. London: Psychology Press. doi:10.4324/9781315696935.
- Proudfoot, D, and Copeland, B. J. (2012). "Artificial Intelligence", in: *The Oxford Handbook of Philosophy of Cognitive Science*, Oxford Handbooks, Eric Margolis, Richard Samuels, and Stephen P. Stich (Eds.). pp. 147–182. <https://doi.org/10.1093/oxfordhb/9780195309799.013.0007>.
- Rumelhart, D. E., and Ortony, A. (2017). "The representation of knowledge in memory", in: *Schooling and the acquisition of knowledge*, R. C. Anderson, R. J. Spiro, and W. E. Montague (Eds.). pp. 99–135. Routledge. <https://doi.org/10.4324/9781315271644> (Original work published in 1977).
- Saariluoma, P. (1995). *Chess players' thinking*. London: Routledge.
- Saariluoma, P. (1997). *Foundational analysis: Presuppositions in experimental psychology*. London: Routledge.

- Saariluoma, P. (2022). Mental Content and Content-Based Cognitive Ergonomics, *Ergonomics International Journal*, 6(2), 000289. <https://doi.org/10.23880/eoij-16000289>
- Saariluoma, P., Cañas Delgado, J. J., and Myllylä, M. (2024). "Problems of content-based cognitive ergonomics", in: *Human Systems Engineering and Design (IHSED2024): Future Trends and Applications. Proceedings of the 6th International Conference of the Human Systems Engineering and Design*. pp. 220–227. AHFE International. AHFE International, 158. <https://doi.org/10.54941/ahfe1005545>
- Saariluoma, P., Karvonen, A. (2024). Theory languages in designing artificial intelligence, *AI & Society*, 39, 2249–2258. <https://doi.org/10.1007/s00146-023-01716-y>
- Salomaa, A. (1985). *Computation and automata* (No. 25). Cambridge: Cambridge University Press.
- Searle, J.R. (1980). Minds, brains, and programs, *Behavioral and Brain Sciences*, 3(3), 417–424. doi:10.1017/S0140525X00005756.
- Turing, A. (1950). Computing machinery and intelligence, *Mind*, LIX, 433–459.
- Turing, A. (2004). "On computable numbers, with an application to the Entscheidungsproblem (1936)", in: *The essential Turing: seminal writings in computing, logic, philosophy, artificial intelligence, and artificial life, plus the secrets of Enigma*, B. Jack Copeland (Ed.). pp. 58–90. Clarendon Press. Original work published in 1936.
- Van Eemeren, F. H., and R. Grootendorst. 2004. *A systematic theory of argumentation: The pragma-dialectical approach*. New York: Cambridge University Press.
- Wickens, C. D. and Carswell, C. M. (2012). "Information processing", in: *Handbook of Human Factors and Ergonomics* (4th ed.), G. Salvendy (Ed.). pp. 206–294. New York: Hoboken John Wiley & Sons, Incorporated.
- Wittgenstein, L. (1953). *Philosophical investigations*. New York: Basil Blackwell.
- Wittgenstein, L. (1961). *Tractatus-Logico Philosophicus*. London: Routledge. Original work published in 1921.
- Woods, D. D., and Hollnagel, E. (2006). *Joint cognitive systems: Patterns in cognitive systems engineering*. Boca Raton: CRC press/Taylor & Francis.
- World Economic Forum (2025a). *AI in action: Beyond experimentation to transform industry. Transformation of Industries in the Age of AI*. Flagship White Paper Series. AI Governance Alliance in collaboration with Accenture. https://reports.weforum.org/docs/WEF_AI_in_Action_Beyond_Experimentation_to_Transform_Industry_2025.pdf
- Xu, W. and Gao, Z. (January–February 2024). Applying HCAI in developing effective human-AI teaming: A perspective from human-AI joint cognitive systems. *Interactions*. <https://doi/10.1145/3635116>.