EMOTIONAL INTELLIGENCE IN EDUCATION: BRIDGING GENERATIVE AI, MODEL CREATION AND PROMPT WRITING

L'INTELLIGENZA EMOTIVA NELL'EDUCAZIONE: UN PONTE TRA LA GENERATIVE AI, LA CREAZIONE DI MODELLI E LA SCRITTURA DI PROMPT

Maria Vittoria Battaglia
Niccolò Cusano University
mariavittoria.battaglia@unicusano.it

Francesco M. Melchiori
Niccolò Cusano University
francesco.melchiori@unicusano.it

Double Blind Peer Review

Citazione
Battaglia, M.V., & Melchiori, F.M. (2024). Emotional intelligence in education: bridging generative ai, model creation and prompt writing. *Italian Journal of Health Education, Sports and Inclusive Didactics*, 8(2), Edizioni Universitarie Romane

Doi:
https://doi.org/10.32043/gsd.v8i3.1112

gsdjournal.it
ISSN: 2532-3296
ISBN 978-88-7730-494-0

ABSTRACT
The article explores the analogy between mental modelling and prompt writing, positing that emotions, which are integral to the formation of mental models, may also influence prompt writing for genAI. The potential interplay between models, prompts and emotions is analysed to advocate for the development of students' EQ as a means of enhancing their modelling skill and effectiveness of prompt writing, suggesting new directions for empirical research.

L'articolo esplora l'analogia tra la creazione di modelli mentali e la scrittura di prompt, ipotizzando che le emozioni, centrali nella formazione dei modelli, possano influenzare anche la scrittura di prompt per la generativeAI. Si analizza la possibile interazione tra modelli, prompt ed emozioni per suggerire lo sviluppo dell'IE degli studenti come mezzo per migliorare la capacità di modellizzazione e l'efficacia della scrittura di prompt, suggerendo nuove direzioni per la ricerca empirica.

KEYWORDS
Emotional Intelligence, Generative AI, Prompt writing, Mental models, model design
Intelligenza emotiva, Generative AI, Prompt writing, Modelli mentali, modellizzazione

Received 30/04/2024
Accepted 13/06/2024
Published 24/06/2024

Introduction

The advent of generative artificial intelligence (AI) heralds a transformative era in human-computer interaction. The nuanced art of prompt engineering is increasingly recognized as critical to eliciting desired responses from AI systems. This paper explores the intricate nexus between mental models, prompt engineering, and emotional intelligence (EQ), positing that EQ significantly shapes the formulation of effective prompts (Beyond the Arc, 2024). The proposed theoretical reflection adopts a method similar to Benjamin's *constellation,* which considers diverse and seemingly unrelated topics with the goal of forging connections between them.
The discourse begins with an exploration of scientific research on the construction of theoretical or mental models, as discussed in the first section. These models are considered essential to learning and scientific research (Giere, 2004). Mental models represent an epistemological theory that elucidates reasoning and cognition from the ability to represent information and thereby create mental simulations of the world. Such capabilities are essential for writing prompts for generative AI systems. The various approaches, such as role-playing, interview patterns, or tree-of-thought, and their various components are examined in the following section.
Prompt writing serves as a conduit between human intentions and AI capabilities. Effective use of this skill requires a collaborative, bidirectional approach in which interactive, iterative dialogue improves performance and outcomes. Thus, the creation of accurate prompts requires the same cognitive skills as mental model creation, including semantic encoding, cognitive load minimization, and envisioning. In both mental model creation and prompt writing, an essential phase is the evaluative stage, which involves a self-regulatory and metacognitive component that is related to emotional intelligence (Tzohar-Rosen & Kramarski 2014). Numerous studies highlight the influence of emotions on model formation and accuracy (Benoit et al., 2019; Holmes, Matthews 2010; Bless, 2000; Stangl, 2012) and the input-output process of generative AI (Cheng et al., 2023a; 2023b; Muranaka et al. 2023; Jeong, Makhmud, 2023). While EmotionPrompt techniques have demonstrated potential for improving AI performance (Cheng et al., 2023a; 2023b), concerns about the possibility of emotional manipulation exacerbating disinformation raise ethical considerations (Vinay et al., 2024).

This paper contributes to the discourse by examining the role of EQ in prompt engineering and its implications for the ethical development of AI technologies. It does so by exploring the potential configurations of the triadic relationship between the process of creating mental models, the process of writing prompts, and emotions.

1. Mental Models

«*How do we think?*
One answer is that we rely on mental models» (Johnson-Laird, 2004).
The theory of mental models is an epistemological theory mainly associated with the name of the psychologist Johnson-Laird (1980; 1983; 2005) that seeks to describe a peculiar aspect of human cognition, namely the capacity that allows us to interpret and interact with the external world by virtue of a mental representation of information. This capacity is the construction of mental models, defined as long-term abstract cognitive structures that individuals use to describe and explain the world around them (Johnson-Laird, 1983; 2005). Such models are visual mental representations formed from external stimuli and in analogy to what they represent (Johnson-Laird, 1983; 2005) they are based on mental imagination and constructed through processes of visualisation, integration of prior knowledge, simulation and anticipation of possible modifications and changes in the theoretical model (Toon, 2016). They are considered fundamental in learning and scientific research (Giere, 1988; 2004) as their visual and analogue structure makes them manipulable tools for arriving at problem solutions (Hemforth, 2006). Johnson-Laird and Khemlani (2014) state that human beings can reason logically and infer probabilities because they can create simulations of the world and such simulations are precisely mental models, which by virtue of their imitative and analogical character (Gentner 2001) allow reasoning about situations that are not directly experienced.
From these definitions, it emerges that mental models, by virtue of their structurally analogical and topological nature, are systems that include possible changes in the state of the represented reality (Borg, Bille, 2019), and for this reason it is possible to modify and change them, adapt them (Van Ments, Treur, 2021) in an iterative manner, to make them ever more precise and accurate, thus preserving the complexity and dynamism of learning, reasoning, in short, knowledge.

2. Prompt engineering

The burgeoning field of generative artificial intelligence requires the cultivation of a specific skill in order to fully realise its potential: prompt writing, or more precisely, prompt engineering. The former refers to the act of writing prompts, while the latter refers to the processes that lead to the design and delineation of prompts. Although a distinction can be made between these two concepts, they are inextricably intertwined, as prompt writing requires the design and development of preliminary prompt strategies.

The prompt serves as the linchpin of human-genAI interaction. It is an input - in the form of an image, video, audio, or natural language text - through which users articulate their requests to the system. Prompt engineering/writing therefore refers to the process of crafting appropriate instructions that anticipate and guide the AI's responses to achieve desired outcomes.

Several mechanisms underpin prompt writing, including semantic encoding-the translation of concepts and information needs into natural language-minimising cognitive load to facilitate decision making, focusing attention and cognitive resources to achieve desired outcomes, and creating mental models that are essential for writing prompts with appropriate framing. *Framing*, or context, is one of the structural components of prompts, along with the *request*, *references* to previous responses or external resources, and *format*.

Among these components, framing is a central, defining aspect of prompt writing. It includes a description of the problem to be solved, its context, and provides the bot with all the information necessary to generate a satisfactory response. Some framing may adopt the role-playing model, with the goal of reducing ambiguity by establishing context in advance. For a more detailed account of different types of framing, see Budiu, Liu, Zhang, Cianca (2023). Establishing framing is a fundamental strategy in prompt engineering because it determines the bot's approach to retrieving and formulating the response.

For example, the most commonly used strategy, especially by less experienced users, is the *naive approach*, a *zero-shot* mode of prompting - i.e., where no examples are provided for the bot to draw from and model its responses on - which involves formulating simple questions without framing, with little detail, thus generating trivial, general, and imprecise responses. The naive approach requires minimal effort in prompting, but significant effort in conversation, as more questions must be asked to achieve the desired result.

Another approach is the *interview pattern*, which allows the bot to interview the user to obtain precise and detailed information to guide the response. This approach requires considerable cognitive effort and the ability to reverse the perspective, allowing an external actor - in this case, the genAI pattern - to interview the subject based on the subject's own desires, needs, and expectations.

A particularly effective approach is the *persona pattern*, which requires the

aforementioned role-playing model as a framework and takes advantage of the subject's simulative abilities.
The formulation of the prompt can significantly influence the nature of the responses generated by the AI. One can aim for a variety of responses, ranging from general and imprecise - a characteristic of the classic input-output modality derived from a naive approach - to sequential and increasingly precise - *chain of thought* - or even a complex and multifaceted response that closely mimics human reasoning. The latter is embodied in the *tree-of-thought* mode, which encourages the bot to reconsider decisions it has made, to correct itself autonomously, to retrace its steps by exploring different possibilities and considering intermediate thoughts, thereby exploring hypothetical and creative perspectives that may not necessarily lead to the desired solution.
Prompt writing serves as a conduit between human intentions and AI capabilities. Effective use of this capability requires a collaborative, bi-directional approach in which an interactive and iterative dialogue refines the understanding of the prompt and the results. As a result, prompt engineering can be viewed as a creative act and endeavour, a form of storytelling «guiding AI to explore uncharted territories of thought» (Hobson, 2024).

3. Mental models and prompt engineering: two of a kind

According to Johnson-Laird and other proponents of mental model theory, reasoning, and all cognitive operations in general, hinge on representations or simulations of the object or phenomenon under consideration. These operations are cyclical processes wherein a change, failure, or success cannot be anticipated, necessitating strategies such as backtracking and mental simulation of actions (Decety and Grèzes, 2006) to progressively approximate the solution. Newell and Simon (1972) define *problem-space* as a symbolic space representing both the problem and its solution, and they find this problem-solving procedure to be an effective model for intelligent machine problem-solving (Newell, Simon, 2007). Indeed, when employing the *Tree of Thought* prompting approach, it is precisely this procedure that the bot is instructed to execute to generate the output.
In carrying out such cognitive operations and in crafting appropriate prompts, the individual undertakes several steps, including problem identification, planning - i.e., the organisation of sub-goals, intentions, and actions - implementation, and evaluation, which is understood as output monitoring and error adjustments (Miller et al., 2017; Pea, 1982). These operations, which are essential to master prompt engineering, shift the focus of the question to the interaction between the user and

the system (HCI) and the ways in which the user can articulate their intentions so that the bot's tasks, which are invariably goal-oriented, can be accurately developed.
In writing prompts for Large Language Models (LLMs), the user essentially plans the task performance in advance, visualises the objective to be achieved before the task is realised, and envisages all the variables that may contribute to achieving the desired outcome. This imaginative process, defined as *envisioning* (Subramonyam et al., 2024), corresponds to the creation of a mental model concerning the task to be performed, which is ultimately expressed in the form of natural language following an appropriate semantic encoding process. Envisioning is a crucial step in creating a more specific prompt for the LLM: if the goal is a high-quality response, the user can optimally leverage the system's vast knowledge by imagining possible and highly desirable outcomes (Subramonyam et al., 2024).

Writing precise prompts requires the same cognitive skills as creating mental models, because the quality of the output - or model - depends heavily on the clarity, specificity and structure of the input prompt. For these reasons, prompt writing can be conceptualised as a form of modelling. Both prompt writing and the creation of mental models require the activation of a semantic encoding process: to interpret and represent information and/or external stimuli in the case of mental models, and to translate abstract concepts and tasks into natural language in the case of prompts. Both, to be useful and to generate knowledge, must reduce cognitive load by focusing attention on salient details, thereby avoiding cognitive illusions. In addition, both are goal-directed, requiring awareness of the task to be performed or the goal to be achieved. Another characteristic shared by models and prompts is that their production is dynamic, plastic and iterative, requiring modification and adaptation in response to results, experience and learning.
An important aspect that prompt writing and mental model building have in common is *simulation*. Mental models are analogue representations; similarly, an effective prompt may use specific simulative strategies, such as the persona pattern or the role-play model.
This underlines the uniqueness of prompts, which, like mental models, are *knowledge representations.* This term is used in the cognitive field to refer to the way we store, understand and manipulate information in order to use it in the real world or to predict future events. However, it can also be found in the artificial intelligence literature, where it refers to *knowledge-based* AI systems that mimic an information processing model typical of the human mind and could therefore be considered *artificial mental models* (Andrews et al., 2022). An example of an

artificial mental model is the mReasoner, a computational model designed by Johnson-Laird and Khemlani (2014) to simulate mental models. Although it is not generative AI, it is nevertheless an artificial system that simulates human reasoning and, like genAI models, processes information, recognises patterns, predicts possible changes and adapts to them, generating outputs from the received inputs, which are mental models in the first case and prompts in the second.

4. Bridging emotions, Model Creation, and Prompt Writing

An integral stage of reasoning, problem-solving and similar operations is the evaluative stage, which includes an autoregulatory and a metacognitive component. This stage involves comparing the actual outcome of actions with the desired goal, thereby facilitating the planning of subsequent actions (Stanton et al., 2021). Self-regulation and metacognition are linked to EQ (Tzohar-Rosen & Kramarski 2014), suggesting that the latter plays an important role both in the creation of mental models that underpin reasoning and in the planning of prompting strategies to produce satisfactory outcomes.

Numerous studies claim that emotions influence the formation and accuracy of models, as the mental images whose processing and integration constitute the model are inherently linked to the subjective emotional state (Benoit et al., 2019; Holmes, Matthews 2010). However, the scientific community has yet to reach a consensus on the nature of this interaction.

Furthermore, emotions are related to mental models because these models contain certain expectations/thoughts about how things should look/work and associate certain emotions with them. In learning situations, new information is compared with content, including beliefs and emotions, and existing structures; thus, an adapted mental model is generated based on prior knowledge and experience, which includes not only cognitive but also emotional aspects (Stangl, 2012). Just as emotions influence the formation of mental models, recent examples show similar effects in the input-output process of generative AI (Vinay et al., 2024; Cheng et al., 2023a). Current artificial intelligence (AI) systems produce highly accurate results that closely resemble human responses in a variety of contexts. Researchers at Microsoft and the CAS Institute have been studying how these models respond to prompts with emotional input. For example, the *EmotionPrompt* project (Cheng et al., 2023a) explores the potential of using emotional intelligence to improve the performance of these systems, and demonstrates that it is possible to improve the responses of generative artificial intelligence by incorporating emotional language into the prompt (EmotionPrompt, EP). Incorporating emotional

cues into the prompt improved responses by 8-10%, whereas emotional cues in the prompt can reduce performance (Cheng et al, 2023b).
A similar result was observed in a subsequent study (Muranaka et al., 2023), which examined the change in ChatGPT responses when emotion-injected rather than neutral prompts were used. Emotions play a crucial role in prompt writing, not in the insertion of emotional cues for the response, but in the framing of person-pattern approaches: by exploiting the potential emotional states of the person, the bot can enhance role-playing skills by generating natural and realistic responses in conversational exchanges (Jeong, Makhmud, 2023).
Several studies have looked at the emotional intelligence of generative AI, or its theory of mind, which is understood as the ability to understand and interpret the mental states of others. Recent models suggest that this ability is comparable to that of humans. For example, in a study by Kosinski (2023), the Large Language Model (LLM) 'text-davinci-003' scored 93% on theory of mind tasks, similar to seven-year-old children. Conversely, Moghaddam and Honey (2023) tested the theory of mind of GPT-4, which scored 100%. Wang et al (2023) compared the results of several LLMs on Emotion Understanding tasks with a sample of 500 adults and found that many models achieved above-average EQ scores. In particular, GPT-4 outperformed even 89% of human participants with an EQ of 117. An interesting aspect of the role of emotion in prompt design lies not so much in the response and operation of the bot, but rather in the prompt definition strategy itself, specifically in the interaction between the user and the model. When writing a prompt for the LLM, the user must consider the context, the details, and a range of information that define the model of the task to be performed. They need to mentally explore the intentions and goals and define them appropriately. Subramonyam et al. (2024) identify among the characteristics of failed prompts the *capability gap*, i.e. «the users' inability to formulate 'how to' procedures to implement their intentions», since «The value of generative outputs depends entirely on the intentions linking goals to their execution in output» (Subramonyam et al., 2024). The author associates this procedure with the creation of a mental representation of the task, «to mentally envision what is required for them to perform the generative task».
Therefore, just as emotional intelligence emerges as a crucial factor in the creation of accurate and effective mental models, if one perceives prompt writing as a form of modelling, one can hypothesise that emotional intelligence is a fundamental competence in the development of the ability to write accurate prompts that yield the desired outcomes. If emotional intelligence plays a role in mental modelling and prompt writing for generative AI, it is worthwhile to contemplate the possible configurations of this triadic relationship. In one possible configuration, these three

components - emotions, mental models and prompts - are linked in a cyclical way. In this model, emotions influence the creation of mental models, which in turn influence the way prompts are written. This process can further develop students' emotions, creating a feedback loop between the components. In this configuration, mental models are seen as a *process* (Hemforth, 2006) that not only leads to the development of effective prompts, but also promotes growth in both knowledge and emotional intelligence.

An alternative configuration might be a hierarchical model that positions emotional intelligence as the foundation upon which both the mental model and the prompt rest. This scaffolding enables the activation of cognitive processes that *produce* (Hemforth 2006) both the mental model and the prompt. In this case, they are not dependent on each other, but correlate by having the same predictor.

Yet another interpretation positions emotional intelligence as a moderator within a model that then determines 'when' the relationship between mental model creation and the writing of effective prompts occurs. Under certain conditions, these are dependent on - and not analogous to - the mental models.

Determining the configuration from a structural perspective is a complex task, but it can be asserted that from a functional perspective, each of these possible configurations implies a relationship, either direct or indirect, between the three components discussed in this article, i.e. mental models, prompts and emotions. The interrelationship between these components is central to cognition, as mental models underpin the processes of reasoning, understanding, decision making and problem solving (Figure 1). Similarly, the ability to write clear, precise, detailed and accurate instructions is a skill that requires the activation of significant cognitive processes.

The implications of these suggestions point to the potential importance of educating students' emotional intelligence to enhance their ability to create mental models and write effective prompts. This perspective opens new avenues for integrating emotional intelligence into the educational context, providing practical tools to improve learning and communication in academic settings.

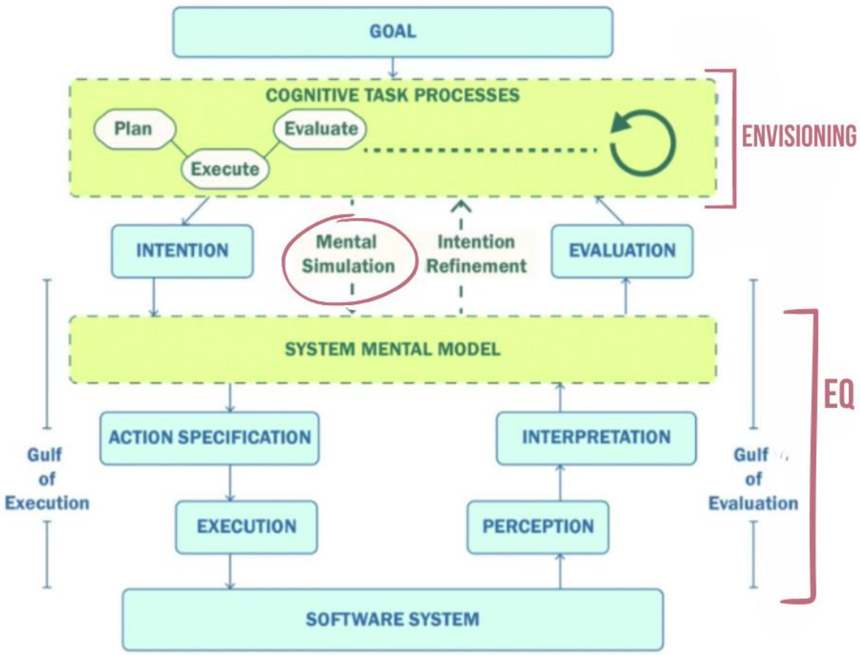

Figure 1. User-system interaction for task resolution (Subramonyam et al., 2024), can be understood as representative of a potential configuration of the relationship between models, prompt writing, and emotional intelligence.

Conclusions

Ultimately, the exploration of mental models, prompt writing, and emotional intelligence in this paper highlights the complex interplay between emotions and cognitive processes in generative AI interactions. Recognizing the role of emotions in mental model formation and prompt writing reveals a new facet of AI engagement that underscores the value of emotional intelligence. However, it is critical to acknowledge the limitations of current AI systems in truly understanding and replicating the depth of human emotions. Indeed, while emotions play a critical role in mental model formation, the limitations of generative AI must be acknowledged. It cannot experience emotions, so its responses are constructed without emotional context. Furthermore, the effectiveness of prompt writing is tied to the AI's predefined capabilities and rules, as it could operate within a framework that ensures safety and relevance without personal opinions or emotions. Another consideration is the dynamic nature of mental models, which allows for continuous refinement. In contrast, the adaptability of generative AI is inherently limited by its programming and the data available up to a certain point in time. Finally, while enhancing students' emotional intelligence has the potential to enhance their modelling abilities, it is imperative to carefully weigh the ethical considerations and establish clear boundaries when integrating such skills into AI interactions. While the integration of emotional cues can lead to more human-like interactions, AI still lacks the true emotional understanding and empathy that characterises human interactions. This understanding not only improves our ability to create prompts, but also suggests exciting directions for future research.

References

Andrews R.W., Lilly J.M., Srivastava D., Feigh K.M. (2023), *The role of shared mental models in human-AI teams: a theoretical review*. Theoretical Issues in Ergonomics Science, 24(2), 129–175.

Benoit R.G., Paulus P.C., Schacter D.L. (2019), *Forming attitudes via neural activity supporting affective episodic simulations*. Nature Communications, 10, 1-11.

Beyond the Arc. (2024), *Prompt engineering best practices: Emotional Intelligence in AI*. Retrieved from:

https://beyondthearc.com/blog/2024/ai-ml/emotional-intelligence-in-ai-prompt-engineering-best-practices

Bless H. (2000), *The interplay of affect and cognition?: the mediating role of general knowledge structures.* In J.P. Forgas (ed.), *Feeling and Thinking?: Affective Influences on Social Cognition,* 201–222. New York: Cambridge University Press.

Borg D., Bille L., (2019), *The Architecture of Mental Models.* Retrieved from: https://www.linkedin.com/pulse/architecture-mental-models-linus-bille/

Budiu R., Liu F., Zhang A., Cianca E. (2023), *Prompt Structure in Conversations with Generative AI.*

Retrieved from: https://www.nngroup.com/articles/ai-prompt-structure/

Cheng L., Jindong W., Yixuan Z., Kaijie Z., Wenxin H., Jianxun L., Fang L., Qiang Y., Xing X. (2023a), *Large Language Models Understand and Can Be Enhanced by Emotional Stimuli*. arXiv:2307.11760

Cheng L., Jindong W., Yixuan Z., Kaijie Z., Xinyi W., Wenxin H., Jianxun L., Fang L., Qiang Y., Xing, X. (2023b). *The Good, The Bad, and Why: Unveiling Emotions in Generative AI*. arXiv:2312.11111v2

Decety J., Grèzes J. (2006), *The power of simulation: imagining one's own and other's behavior*. Brain Research, 1079(1), 4-14.

Gentner D. (2001), *Psychology of Mental Models.* In International Encyclopedia of the Social & Behavioral Sciences.

Giere R. (1988), *Explaining Science*. Chicago: University of Chicago Press.

Giere R. (2004), *How models are used to represent reality*. Philosophy of Science, 71, 742-52.

Hemforth B. (2006), *Language Processing: Construction of Mental Models or More?* Advances in Psychology: Mental Models and the Mind - Current Developments in Cognitive Psychology, Neuroscience, and Philosophy of Mind, 138, 189–204.

Hobson J.K. (2024), *Demystifying Prompt Engineering: Unveiling the Art Behind Effective AI Communication.* Retrieved from:

https://www.linkedin.com/pulse/demystifying-prompt-engineering-unveiling-art-behind-effective-20t5c

Holmes E.A., Matthews A. (2010), *Mental imagery in emotion and emotional disorders*. Clinical Psychology Review, 30, 349-362.

Jeong S., Makhmud. A. (2023), *Chatbot is not all you need: information-rich prompting for more realistic responses.* arXiv:2312.16233

Johnson-Laird P.N. (1980). *Mental models in cognitive science.* Cognitive Science, 4(1), 71–115.

Johnson-Laird P.N. (1983), *Mental Models. Towards a Cognitive Science of Language, Inference and Consciousness*. Cambridge, UK: Cambridge University Press.

Johnson-Laird P.N. (2001), *Mental models and deduction*. Trends in Cognitive Science, 5, 434-442.

Johnson-Laird P.N. (2004), *The History of Mental Models*. London, New York: Routledge.

Johnson-Laird P.N. (2005), *Mental Models and Thought*. In K.J. Holyoak, R.G. Morrison (Eds.), *The Cambridge Handbook of Thinking and Reasoning*, 185-208. Cambridge: University Press.

Johnson-Laird P.N., Khemlani S. (2014), *Toward a unified theory of reasoning.* Psychology of Learning and Motivation, 59, 1-42.

Kosinski M. (2023), *Evaluating Large Language Models in Theory of Mind Tasks.* arXiv:2302.02083

Miller G.A., Galanter E., Pribram K.H. (2017), *Plans and the Structure of Behaviour.* Systems Research for Behavioral Science. London, New York: Routledge, 369–382.

Moghaddam S.R., Honey C.J. (2023), *Boosting Theory-of-Mind Performance in Large Language Models via Prompting*. arXiv:2304.11490

Muranaka S., Fukatsu T., Takebayashi Y., Kunugi M., Nakajima S., So R. (2023), *Emotion-injecting prompt for large language model chatbot*. PREPRINT. Retrieved from: https://osf.io/preprints/psyarxiv/u5dft

Newell A., Simon. H.A. (2007), *Computer science as empirical inquiry: Symbols and search*. In ACM Turing award lectures 1975. New York: Association for Computing Machinery

Newell A., Simon. H.A. (1972), *Human problem solving*. Englewood Cliffs, NJ: Prentice-hall

Pea R.D. (1982), *What is planning development the development of?* New Directions for Child and Adolescent Development, 18, 5–27.

Rehkämper K. (2006), *Pictures, Perception, and Mental Models.* Advances in Psychology: Mental Models and the Mind - Current Developments in Cognitive Psychology, Neuroscience, and Philosophy of Mind, 138, 157–172.

Robinson M.D., Asda M.R., Irvin R.L. (2023), *Emotional intelligence as evaluative activity: theory, findings and future directions*. J Intell, 11(6), 125.

Stangl, B. (2012). *Emotional Mental Models*. In: Seel, N.M. (eds) *Encyclopedia of the Sciences of Learning.* Boston: Springer.

Stanton J.D., Sebesta A.J., Dunlosky J. (2021), *Fostering Metacognition to Support Student Learning and Performance*. CBE Life Sci Educ. 20(2).

ubramonyam H., Pea R., Pondoc C.L., Agrawala M., Seifert C. (2024), *Bridging the Gulf of Envisioning: Cognitive Challenges in Prompt Based Interactions with LLMs.* arXiv:2309.14459v2

Toon A. (2016), *Imagination in scientific modeling*. In A. Kind (Ed.), *The Routledge Handbook of Philosophy of Imagination*. London, New York: Routledge.

Tzohar-Rosen M., Kramarski B. (2014), *Metacognition, motivation and emotions: Contribution of self-regulated learning to solving mathematical problems.* Global Education Review, 1(4). 76-95.

Van Ments L., Treur J. (2021), *Reflections on dynamics, adaptation and control: A cognitive architecture for mental models.* Cognitive Systems Research, 70, 1-9.

Vinay R., Spitale G., Biller-Andorno N., Germani F. (2024), *Emotional Manipulation Through Prompt Engineering Amplifies Disinformation Generation in AI Large Language Models*. arXiv:2403.03550.

Wang X., Li X., Yin Z., Wu Y., Liu J. (2023), *Emotional intelligence of Large Language Models.* Journal of Pacific Rim Psychology, 17.