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(Review Article)

Exploring cognitive reflection for decision-making in robots: Insights and implications

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Abstract

This study critically examines the potential of embedding a cognitive reflection model within robotic decision-making systems. Cognitive reflection, which enables humans to surpass initial impulses and heuristics for improved decision outcomes, is proposed as a mechanism to augment the decision-making capacity of autonomous robots. By analyzing existing decision-making paradigms in robotics, this paper conceptualizes the adoption of cognitive reflection and evaluates its prospective transformative impact on the field. Through a detailed investigation, it articulates the significant enhancements in robotic intelligence and functionality that cognitive reflection can offer. Furthermore, it rigorously discusses the technical feasibility, ethical considerations, and broader societal ramifications, delineating a comprehensive framework for the responsible and effective integration of cognitive processes in robotics.

Keywords: Cognitive Reflection; Decision-Making; Robotic Autonomy; Adaptive Robotics

1. Introduction

In contemporary robotics, decision-making predominantly relies on deterministic algorithms and advanced machine-learning strategies. These methodologies have significantly advanced the field, granting robots a level of autonomy previously unimaginable [1,2]. Despite these advancements, limitations become evident, particularly in scenarios demanding nuanced judgment and adaptability akin to human cognition [3]. This disparity not only delineates the current boundaries of robotic intelligence but also highlights the immense potential for pioneering progress. The principle of cognitive reflection, integral to human reasoning, presents a viable pathway to address these limitations [4]. In humans, cognitive reflection facilitates the reassessment of initial, often instinctive responses, leading to more deliberate and potentially more accurate decisions [5]. Transferring this capability to robots could considerably enhance their decision-making abilities, especially in complex and unpredictable environments where heuristic shortcuts and pre-programmed responses are insufficient [6]. Incorporating cognitive reflection into robotic systems, however, poses significant challenges [7]. It necessitates a reexamination of existing computational models and the investigation of new frameworks that can support the complexity and flexibility of reflective thinking [8]. This effort requires a multidisciplinary approach, leveraging insights from cognitive psychology, artificial intelligence, and ethics to overcome the theoretical and practical obstacles involved [9].

Paper Overview: This paper undertakes a thorough investigation into integrating cognitive reflection into robotic decision-making. Through a detailed examination of existing decision-making mechanisms in robotics and an identification of their limitations, a new conceptual framework is proposed, aimed at enhancing robotic autonomy and adaptability [10]. The subsequent sections explore the technical basis for this integration, the expected transformative effects on robotic capabilities, and the broader societal and ethical implications [11]. Through this examination, the paper seeks to establish a foundation for future research and development in the field, aiming for robots that can engage in reflective, informed decision-making, moving beyond mere task execution [12]

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2. Literature Review

2.1. Historical Development of Decision-Making in Robotics

The historical tapestry of robotic decision-making is woven with threads of innovation and technological milestones that have progressively shaped the autonomy of robots. In the nascent stages, the focus was primarily on embedding simple algorithms that allowed robots to autonomously carry out basic tasks based on preset rules and limited sensory inputs. This period was marked by an exploration into the rudimentary autonomy of robots, setting the stage for more advanced interactions with their environments [13].

With the dawn of the 1990s, a significant paradigm shift occurred as adaptive decision-making systems began to take center stage. This era was defined by the incorporation of learning algorithms, signifying a substantial step toward enhancing robotic autonomy beyond static programming. It marked a pivotal moment where robots started to adjust their behavior in response to environmental changes and task variations, showcasing an embryonic form of contextual awareness and adaptability [14].

The infusion of biologically inspired models into robotics marked another revolution, offering a fresh perspective on decision-making processes. By emulating the intricate behaviors and cognitive functions observed in the animal kingdom, these models endowed robots with the ability to navigate and interact with their surroundings in more sophisticated and intelligent ways. This approach not only broadened the potential applications for robotics but also challenged previous notions of robotic capabilities [15].

The integration of machine learning and artificial intelligence has since propelled the field into a new era, enabling robots to make decisions in real-time with a degree of complexity and adaptability previously unattainable. This phase is characterized by the creation of systems capable of synthesizing data, learning from past experiences, and responding to environmental cues, heralding a new age of context-aware and adaptive robotic autonomy [16,17]

2.2. Current Decision-Making Models and Algorithms

Today's landscape of robotic decision-making is a mosaic of diverse models and algorithms designed to navigate the myriad challenges inherent in autonomous and social robotics. Among these, reinforcement learning has emerged as a keystone, providing a framework within which robots can refine their decision-making through experiences, mirrored in a cycle of actions, rewards, and subsequent adaptations [18,19]. This method has shown remarkable versatility, facilitating both simple and complex behavioral modifications.

Probabilistic models, such as Bayesian networks and Markov decision processes, have established themselves as essential tools in the roboticist's arsenal, adept at managing uncertainty in dynamic environments [20]. By adopting a probabilistic approach to decision-making, these models offer a nuanced way to make informed decisions amidst the inherent unpredictability of real-world scenarios.

The advent of neural networks, especially through deep learning advancements, has significantly influenced pattern recognition and decision-making in robotics [21]. These algorithms excel at deciphering complex, multifaceted data, enabling robots to undertake tasks that require deep understanding and flexible problem-solving capabilities.

Hybrid models that meld rule-based systems with machine learning innovations represent a strategic fusion aimed at optimizing decision-making efficacy [22]. By harnessing the reliability of deterministic models and the adaptability of learning-based approaches, these hybrid systems aim to strike a balance that leverages the strengths of both paradigms. Despite the progress, challenges such as scalability, interpretability, and the harmonious integration of varied data types persist, catalyzing continuous research and development efforts in the quest for more refined and capable robotic decision-makers.

This narrative of evolution from simple algorithms to complex adaptive systems encapsulates the ongoing journey of robotic decision-making. Each advancement not only extends the operational capabilities of robots but also propels the entire field towards a future where robots are envisioned as central players in solving multifaceted societal challenges.

2.3. Biologically Inspired Models and Machine Learning in Robotics: Discussion on the integration of natural decision-making processes and AI advancements

The fusion of biologically inspired models with machine learning methodologies in the realm of robotics marks a significant leap forward in refining the decision-making capabilities of robotic systems. This integration draws from the intricate decision-making processes inherent in natural systems, coupled with the advancements in artificial intelligence, to cultivate robots that demonstrate enhanced adaptability and sophisticated behavior.

Biologically inspired frameworks, notably Artificial Neural Networks (ANN) and Genetic Programming (GP), have played a pivotal role in advancing robots' ability to accurately learn spatial object localization through vision inputs on humanoid robots [23]. These approaches emulate the cognitive processes observed in biological entities, thus endowing robots with the intelligence to navigate and interact within their environments in a more nuanced manner.

Furthermore, machine learning techniques, such as Probabilistic Neural Networks, have emerged as effective tools for modeling the complexity inherent in robotic systems. These methodologies have significantly contributed to increasing task accuracy and reducing uncertainty in robotic manipulators [24], underscoring the potential of machine learning to navigate the complexities of real-world scenarios and enhance robotic decision-making processes.

The implementation of reinforcement learning in the development of humanoid robots illustrates a profound impact on the design and learning strategies of robots, enabling them to autonomously solve problems without direct human oversight [25]. This approach facilitates a form of autonomous learning where robots evolve their decision-making and behaviors based on the outcomes of their actions, epitomized by received rewards, thereby demonstrating an autonomous learning and decision-making capability.

Moreover, the employment of big data and machine learning within cloud robotic architectures heralds the arrival of robots that are not only smarter but also more responsive [26]. By harnessing extensive datasets and sophisticated machine learning algorithms, robots can augment their functionalities, adeptly adapt to changing environments, and execute tasks with heightened efficiency.

In summation, the synergistic integration of biologically inspired models and machine learning in robotics heralds a paradigmatic shift towards the creation of robotic systems endowed with advanced decision-making faculties, adaptability, and intelligence. This integration propels the field of robotics towards the realization of more autonomous and proficient systems, signaling a promising direction for future advancements in robotic technology.

2.4. Challenges and Gaps in Current Robotic Decision-Making

In the intricate landscape of robotics, decision-making processes are met with a range of challenges, especially when functioning within complex and dynamic environments. A significant barrier in this domain is the development of autonomous soft robots, designed for intelligent interaction and adaptation to changing environments without external inputs [27]. The need for these robots to independently navigate through unpredictable and structured terrains underlines a notable deficiency in the current capabilities of robotic decision-making.

Further compounding these challenges are the issues surrounding the specification and verification of autonomous robotic systems, presenting a multitude of both internal and external challenges [28]. Assuring the operational accuracy and reliability of these systems in fluctuating environments remains a conspicuous gap within existing frameworks. Moreover, the complex design and control challenges encountered by indoor autonomous mobile robots highlight the decision-making difficulties in real-time navigation and adjustment [29].

In scenarios necessitating human-robot collaboration, such as rescue missions, designing user interfaces for seamless interaction between human operators and robots presents substantial challenges [30]. Achieving a harmonious blend of human insights with autonomous decision-making processes, especially in urgent scenarios like rescue missions, is particularly challenging. Additionally, applying reinforcement learning in bionic underwater robotics underscores the challenges introduced by complex underwater settings and underactuated systems [31]. The task of effectively training and deploying reinforcement learning algorithms in these environments remains unaddressed in current robotic decision-making strategies. Similarly, multi-robot systems face challenges in sensor fusion-based cooperative trail following, particularly in autonomously identifying man-made trails within natural settings, showcasing the complexities in collective decision-making [32].

These identified challenges and gaps underscore the urgent need for advancements in managing uncertainty, adapting to dynamic environments, integrating human input effectively, and enhancing decision-making processes in complex situations.

2.5. Cognitive-Reflection

Consider this problem: If it takes 5 machines 5 minutes to produce 5 widgets, how long would it take 100 machines to produce 100 widgets? The swift, instinctual reply might be "100 minutes", a reflection of our innate tendency towards immediate conclusions. Yet, a closer, analytical examination reveals the answer to be "5 minutes," underscoring the fundamental shift from instinctive to deliberative thinking. This scenario exemplifies cognitive reflection, the process whereby initial, intuitive judgments are reassessed and refined, thereby arriving at outcomes that are not only more precise but also demonstrably accurate. In other words, cognitive reflection serves as a critical faculty enabling individuals to scrutinize instinctive reactions and delve into more methodical analytical thinking, a cornerstone for effective decision-making and intricate problem-solving. This cognitive trait, as explored by Frederick [1], distinguishes individuals based on their propensity to override initial intuitive responses in favor of more reflective reasoning. Notably, cognitive reflection, as assessed through the Cognitive Reflection Test (CRT), has been substantiated to correlate significantly with various cognitive abilities and skills, including cognitive intelligence, numerical and verbal ability, and even numeracy skills [33].

Dual-process theories, such as those proposed by Kahneman and Frederick [34], delineate human cognition into two distinct systems: System 1, which operates intuitively and automatically, and System 2, characterized by deliberative and analytical processing. Cognitive reflection, thus, is considered a pivotal faculty that modulates the transition from System 1 to System 2 processing, enabling individuals to curb impulsive reactions in favor of more reasoned outcomes.

Empirical investigations have shown mixed findings regarding cognitive reflection's relationship with cognitive intelligence and specific abilities [35]. While some research underscores cognitive reflection's unique contribution to rational thinking and decision-making beyond mere cognitive intelligence [36], others argue that CRT predominantly measures cognitive abilities, particularly numerical reasoning [37], reflecting on CRT's inherent arithmetic problem structure.

Moreover, cognitive reflection's role in education, particularly in understanding scientific principles contrary to intuitive beliefs, has been emphasized [1,38]. Children's performance on CRT-like tests has been linked to their ability to reconcile scientific concepts with intuition, suggesting cognitive reflection's broader implications beyond adulthood, encompassing developmental aspects of learning and cognition.

Despite these insights, the CRT's psychometric limitations, such as its non-normal distribution and modest internal consistency, warrant caution and suggest the necessity for additional, more reliable items to enhance its diagnostic utility [4]. The ongoing debate regarding the CRT's measurement fidelity and its exact role within the cognitive architecture—whether as an independent rationality factor or a subsidiary factor within a hierarchical model of cognitive intelligence—remains unresolved [39–42]. Consequently, the precise delineation of cognitive reflection, alongside its measurement and implications across cognitive domains, calls for further empirical scrutiny.

In summation, cognitive reflection emerges as a multifaceted construct intricately tied to both the foundational processes of human reasoning and the nuanced realms of decision-making, problem-solving, and learning. Its exploration continues to unravel the complex tapestry of cognitive abilities, urging ongoing inquiry into its mechanisms, manifestations, and modulations across the lifespan.

2.6. Potential of Cognitive Reflection in Robotics

Incorporating cognitive reflection into robotic decision-making processes addresses the highlighted gaps and challenges by enhancing robots' adaptability, decision-making capabilities, and interactions within complex and dynamic environments. Cognitive reflection allows robots to reflect on their decision-making processes, explore alternative actions, and assess potential outcomes based on accrued experiences. Through cognitive reflection, robots can navigate complex environments with greater autonomy, make decisions that are timely and informed, and seamlessly integrate human input [43].

This capacity for introspection enables robots to extend their decision-making beyond rigid algorithms, allowing for broader contextual consideration and the potential implications of their actions [44]. By adopting cognitive reflection, robots can improve their adaptability and decision-making processes, leading to more efficient and effective operations within challenging environments [45].

Ultimately, the integration of cognitive reflection in robotic decision-making processes marks a pathway toward overcoming existing challenges and gaps. It equips robots with critical thinking, strategic adaptation, and intelligent interaction capabilities in varied and dynamic environments. Through cognitive reflection, robots can ascend to new decision-making heights, enhancing their autonomy and adeptly navigating the complexities of the modern world.

3. Case Studies and Empirical Evidence on Implementing Cognitive Reflection in Robots

In the swiftly evolving field of artificial intelligence, the endeavor to instill robots with cognitive reflection has sparked significant interest and experimentation. By examining case studies and empirical research, we gain invaluable insights into the progress and challenges inherent in this ambitious venture.

3.1.1. Chacón et al. [46]- "Cognitive Interaction Analysis in Human–Robot Collaboration Using an Assembly Task"

This comprehensive review by Chacón et al. scrutinizes the nuanced dynamics of cognitive interactions within human-robot teams, specifically through the lens of assembly tasks. It reveals the profound impact these interactions have on both the efficiency of task performance and the cognitive workload on human participants. The findings not only demonstrate the positive role of robotic systems in enhancing team dynamics but also prompt further investigation into the depth of cognitive reflection versus the simulation of cognitive engagement within these collaborative settings.

3.1.2. Chien et al. [47]- "Attention allocation for human multi-robot control: Cognitive analysis based on behavior data and hidden states"

In this detailed exploration, Chien et al. delve into the cognitive underpinnings of managing attention in human-multi-robot control scenarios. The study posits that equipping robots with the capability for self-reflection can significantly boost the performance of human-robot teams. This enhancement allows human operators to maintain focus on critical tasks without the distraction of constant attention shifts. However, the research raises critical questions regarding the authenticity of cognitive reflection in robots and its comparison to simulated cognitive engagement, suggesting avenues for further scholarly inquiry.

3.1.3. Wang et al. [48]- "Multi-Scale Extension in an Entorhinal-Hippocampal Model for Cognitive Map Building"

Focusing on spatial navigation, this study endeavors to replicate the brain's mapping capabilities within AI models. The innovative approach to cognitive map construction in robots offers a glimpse into potential advancements in simulating complex decision-making processes, akin to those observed in human cognition.

3.1.4. Tsagarakis et al. [49]- "iCub: The Design and Realization of an Open Humanoid Platform for Cognitive and Neuroscience Research"

The iCub platform stands as a testament to the possibilities of cognitive and neuroscience research in robotics. By providing a foundation for the exploration of cognitive architectures, the iCub platform marks a step towards embedding sophisticated cognitive processes in robots. Nevertheless, the research underscores the necessity for continued validation against human cognition to truly achieve an authentic replication of cognitive reflection.

Through the lens of these case studies, we gain valuable insights into the dynamic field of cognitive robotics, showcasing pioneering attempts to imbue robots with cognitive reflection. Each study contributes to our collective understanding, revealing the potential for robots to adopt more human-like cognitive processes. These empirical explorations not only highlight the achievements made but also pinpoint the gaps that future research must address to further advance robotic cognition.

4. Methodologies

4.1. Conceptual Framework for Cognitive Reflection in Robotics

This framework seeks to integrate the lessons learned from practical implementations with theoretical perspectives, offering a structured approach to enhancing cognitive reflection in robots. As we embark on this next phase, our goal is to craft a cohesive narrative that not only encapsulates the current state of cognitive robotics but also charts a course for its future evolution, opening new avenues for research and application in this burgeoning field.

4.1.1. Specific Modular Cognitive Architecture:

- **Integration of Perception and Action Modules**: Enhancing robotic systems with architectures that closely integrate perception and action modules is critical for simulating cognitive reflection. Such integration supports real-time decision-making and processing. [50]

4.1.2. Practical Theoretical Integration

- **Application-Oriented Theoretical Insights**: The application of theoretical insights from cognitive science into robotics has shown practical utility in enhancing robot decision-making and interaction [51].

4.1.3. Advanced Learning and Memory Systems

- **Real-Time Learning and Scalable Memory Systems**: Developing learning and memory systems that are both scalable and capable of real-time processing is crucial for robotic cognitive reflection [52,53]

4.1.4. Computational Efficiency and Scalability

- **Optimization Techniques for Reflective Processes**: Optimization techniques are essential for managing the computational demands of integrating cognitive reflection into robots [54].

4.1.5. Nuanced Approach to Ethical Decision-Making:

- **Dynamic Ethical Frameworks**: Implementing dynamic ethical frameworks in robotic systems can guide them in making decisions that adapt to changing circumstances [55].

4.1.6. Realistic Social Cognition and Interaction:

- **Enhancing Social Cognition:** Integrating insights from psychology, social cognition, and human-robot interaction into robotics, as shown by Phan et al. [56], Cross & Ramsey [57], and Binney & Ramsey [58], is critical for equipping robots with the capability for genuine social cognition and interaction, enabling them to engage in interactions that reflect a deep understanding of human cognitive and emotional dynamics.

4.1.7. Bounded Empathy and Social Understanding

- Recognizing the limitations in current robotic systems to fully replicate human empathy and social understanding is crucial.

4.2. Proposed Methodologies for Implementing Cognitive Reflection in Robots

- *Bayesian Networks for Modeling Uncertainty*: Utilizing Bayesian networks offers a probabilistic approach to encapsulate the uncertainty that robots face in dynamic environments. This method enables a reflective mechanism whereby robots can revise their beliefs and decisions considering new evidence, akin to human cognitive adaptation to uncertainty [59].

- *Reinforcement Learning with Emotion Modules*: Incorporating emotion modules within reinforcement learning frameworks introduces an affective dimension to robotic learning. This integration allows robots to assess decisions not only based on logical outcomes but also considering emotional valences, mirroring the human process of decision-making influenced by emotional states [60–62].

- *Deep Learning with Reasoning Modules*: Augmenting deep learning algorithms with reasoning modules enables robots to transcend mere pattern recognition. By embedding logical deduction and problem-solving capabilities, robots can engage in a more sophisticated form of cognitive reflection, analyzing and understanding their actions and surroundings in a comprehensive manner [63].

- *Fuzzy Logic Systems for Human-Like Reasoning*: Applying fuzzy logic systems allows robots to navigate decision-making processes with a degree of ambiguity and imprecision reflective of human reasoning. This approach empowers robots to make nuanced decisions in situations where information is incomplete or unclear, facilitating a more adaptable and human-like decision-making process [64].

5. Discussions

5.1. Navigating Methodological Hurdles

- *Computational Cost*: The complexity inherent in implementing cognitive reflection raises significant computational challenges. Strategies to mitigate these include the development of more efficient algorithms and the leveraging of advanced computational architectures to facilitate the depth of cognitive processing within the constraints of real-time operational needs [65–67].

- *Validation Against Human Cognitive Processes*: A fundamental challenge lies in aligning robotic cognitive reflection with human cognitive processes. This requires not only the development of sophisticated models that accurately emulate human thought but also interdisciplinary efforts to validate these models against the nuances of human cognition [68–70].

- *Ethical Considerations*: The advancement of robots capable of cognitive reflection brings to the forefront ethical considerations regarding autonomy, decision-making, and the moral implications of their actions. Ensuring that robots' reflective decision-making adheres to ethical standards necessitates the formulation of comprehensive guidelines and principles to guide their behavior in ethically charged situations [71].

In essence, the endeavor to imbue robots with cognitive reflection is as much about enhancing their operational capabilities as it is about redefining the ethical and philosophical boundaries of their integration into human-centric environments. Through careful consideration of the computational, validation, and ethical challenges, this ambitious pursuit can lead to the development of robots that not only act but reflect—a hallmark of truly intelligent systems.

5.2. Practical Implications

The practical implications of integrating cognitive reflection into robotic systems span across multiple domains, offering significant advancements and enhancements:

- **Enhanced Customer Acceptance in Service Industries**: The framework proposed by Shah et al. [72] enhances customer acceptance of AI service robots in restaurants, suggesting a diagnostic tool for improving service quality and satisfaction.

- **Advancements in Developmental Robotics**: Cangelosi & Schlesinger [73] discuss the contribution of developmental robotics to understanding human development and enhancing robotic learning, emphasizing the autonomous acquisition of sensorimotor and cognitive capabilities.

- **Improved Human-Robot Collaboration**: Damiano & Dumouchel [74] explore the role of anthropomorphism in human-robot co-evolution, highlighting its significance in fostering effective collaboration between humans and robots.

- **Enhanced Healthcare Services**: Mahmood et al. [75] outline the potential of robots in assisted living environments, pointing towards improvements in healthcare services and support for individuals.

- **Enhanced Human-Robot Interaction**: Nuovo et al. [76] demonstrate the potential of assessing cognitive skills through human-robot interaction, leading to more personalized and interactive experiences.

- **Improved Social Robotics:** Lanillos et al. [77] showcase the development of an artificial attention system for social robots, facilitating coherent behavior and effective human interactions.

- **Advancements in Cognitive Robotics:** Nakamura et al. [78] present the SERKET architecture, offering insights into large-scale cognitive model realization in robots.

- **Enhanced Learning Experiences**: Tikhanoff et al. [79] highlight the potential of robots to learn complex actions through interaction, improving learning experiences and skill acquisition.

5.3. Future Directions

The evolution of cognitive robotics opens up various future research directions:

- **Ethical Considerations in Human-Robot Interaction**: Ryan et al. [80] and Manzotti & Chella [81] stress the importance of addressing ethical issues in the development and deployment of cognitive robotic systems.

- **Enhancing Learning Experiences with AI and Robotics**: Salas-Pilco [81] proposes focusing on the impact of AI and robotics on learning outcomes, emphasizing the need for enhancing educational experiences.

- **Advancements in Artificial Consciousness**: Szczepanowski et al. [82] explore the potential of implementing artificial consciousness in robots, aiming to understand its impact on cognitive processes.
- **Enhancing Human-Robot Collaboration**: Gutierrez and Steinbauer-Wagner [83] emphasize developing a meta-architecture for robot autonomy to facilitate high-level cognitive abilities in robots.
- **Incorporating Neurophysiological Principles**: Alvarez et al. [84] suggest implementing neurophysiological principles in robotic control interfaces, presenting a direction for future research.

6. Conclusion

This article navigates through the integration of cognitive reflection in robotic decision-making, highlighting how traditional reliance on algorithms and machine learning faces challenges in unpredictable environments. It introduces cognitive reflection as a promising approach to mimic human-like decision-making, enriching robots' responses to complex situations. A detailed review traces the evolution of robotic decision-making, underscoring the potential of cognitive reflection to address existing limitations. By examining case studies and proposing a conceptual framework, the discussion opens pathways for future research focused on creating more autonomous and intelligent robots. This exploration emphasizes the necessity for ethical considerations and practical applications, aiming to equip robots with the capability for reflective and informed decision-making in our increasingly complex world.

References

[1] Frederick S. Cognitive Reflection and Decision Making. J Econ Perspect [Internet]. 2005 Nov 1 [cited 2024 Mar 13];19(4):25–42. Available from: https://pubs.aeaweb.org/doi/10.1257/089533005775196732

[2] Lebiere C, Jentsch F, Ososky S. Cognitive Models of Decision Making Processes for Human-Robot Interaction. In: Shumaker R, editor. Virtual Augmented and Mixed Reality Designing and Developing Augmented and Virtual Environments. Berlin, Heidelberg: Springer; 2013. p. 285–94.

[3] Sinayev A, Peters E. Cognitive reflection vs. calculation in decision making. Front Psychol [Internet]. 2015 May 7 [cited 2024 Mar 13];6. Available from: http://journal.frontiersin.org/Article/10.3389/fpsyg.2015.00532/abstract

[4] Campitelli G, Labollita M. Correlations of cognitive reflection with judgments and choices. Judgm Decis Mak [Internet]. 2010 Jun [cited 2024 Mar 14];5(3):182–91. Available from: https://www.cambridge.org/core/journals/judgment-and-decision-making/article/correlations-of-cognitive-reflection-with-judgments-and-choices/2EA5389B4D2E8840B485E55BD3ED0B47

[5] Terziyan V, Gryshko S, Golovianko M. Patented intelligence: Cloning human decision models for Industry 4.0. J Manuf Syst [Internet]. 2018 Jul 1 [cited 2024 Mar 14];48:204–17. Available from: https://www.sciencedirect.com/science/article/pii/S0278612518300608

[6] Mastrogiorgio A. Commentary: Cognitive reflection vs. calculation in decision making. Front Psychol [Internet]. 2015 Jul 3 [cited 2024 Mar 14];6. Available from: https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2015.00936/full

[7] Ho MK, Griffiths TL. Cognitive Science as a Source of Forward and Inverse Models of Human Decisions for Robotics and Control. Annu Rev Control Robot Auton Syst [Internet]. 2022 [cited 2024 Mar 14];5(1):33–53. Available from: https://doi.org/10.1146/annurev-control-042920-015547

[8] Juanchich M, Dewberry C, Sirota M, Narendran S. Cognitive Reflection Predicts Real-Life Decision Outcomes, but Not Over and Above Personality and Decision-Making Styles. J Behav Decis Mak [Internet]. 2016 [cited 2024 Mar 14];29(1):52–9. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/bdm.1875

[9] Miyazawa K, Horii T, Aoki T, Nagai T. Integrated Cognitive Architecture for Robot Learning of Action and Language. Front Robot AI [Internet]. 2019 Nov 29 [cited 2024 Mar 14];6. Available from: https://www.frontiersin.org/articles/10.3389/frobt.2019.00131

[10] Huang K, Ma X, Song R, Rong X, Li Y. Autonomous cognition development with lifelong learning: A self-organizing and reflecting cognitive network. Neurocomputing [Internet]. 2021 Jan 15 [cited 2024 Mar 14];421:66–83. Available from: https://www.sciencedirect.com/science/article/pii/S0925231220314351

[11] Wang Y. Cognitive Learning Methodologies for Brain-Inspired Cognitive Robotics. Int J Cogn Inform Nat Intell IJCINI [Internet]. 2015 [cited 2024 Mar 14];9(2):37–54. Available from: https://www.igi-global.com/gateway/article/www.igi-global.com/gateway/article/137751

[12] Mutlu B, Roy N, Šabanović S. Cognitive Human–Robot Interaction. In: Siciliano B, Khatib O, editors. Springer Handbook of Robotics [Internet]. Cham: Springer International Publishing; 2016 [cited 2024 Mar 14]. p. 1907–34. Available from: https://doi.org/10.1007/978-3-319-32552-1_71

[13] Aleksander I. Advanced IT: Decision Aids for Robotics. J Inf Technol [Internet]. 1986 Jun 1 [cited 2024 Mar 14];1(2):46–54. Available from: https://doi.org/10.1057/jit.1986.23

[14] Kowalczuk Z, Czubenko M. Intelligent decision-making system for autonomous robots. Int J Appl Math Comput Sci [Internet]. 2011 Dec 1 [cited 2024 Mar 14];21(4):671–84. Available from: https://sciendo.com/article/10.2478/v10006-011-0053-7

[15] Maroto-Gómez M, Castro-González Á, Castillo JC, Malfaz M, Salichs MA. A Bio-inspired Motivational Decision Making System for Social Robots Based on the Perception of the User. Sensors [Internet]. 2018 Aug [cited 2024 Mar 14];18(8):2691. Available from: https://www.mdpi.com/1424-8220/18/8/2691

[16] Hasegawa Y. Advances in Robotics and Automation: Historical Perspectives. In: Nof SY, editor. Springer Handbook of Automation [Internet]. Berlin, Heidelberg: Springer; 2009 [cited 2024 Mar 14]. p. 3–4. Available from: https://doi.org/10.1007/978-3-540-78831-7_1

[17] Merlet JP. A Historical Perspective of Robotics. In: Ceccarelli M, editor. International Symposium on History of Machines and Mechanisms Proceedings HMM 2000. Dordrecht: Springer Netherlands; 2000. p. 379–86.

[18] Akalin N, Loutfi A. Reinforcement Learning Approaches in Social Robotics. Sensors [Internet]. 2021 Jan [cited 2024 Mar 14];21(4):1292. Available from: https://www.mdpi.com/1424-8220/21/4/1292

[19] Matarić MJ. Reinforcement Learning in the Multi-Robot Domain. In: Arkin RC, Bekey GA, editors. Robot Colonies [Internet]. Boston, MA: Springer US; 1997 [cited 2024 Mar 14]. p. 73–83. Available from: https://doi.org/10.1007/978-1-4757-6451-2_4

[20] Zhang T, Mo H. Reinforcement learning for robot research: A comprehensive review and open issues. Int J Adv Robot Syst [Internet]. 2021 May 1 [cited 2024 Mar 14];18(3):17298814211007305. Available from: https://doi.org/10.1177/17298814211007305

[21] Brandão B, Lima TD, Soares A, Melo L, Maximo M. Multiagent Reinforcement Learning for Strategic Decision Making and Control in Robotic Soccer Through Self-Play. IEEE Access [Internet]. 2022 [cited 2024 Mar 14];10:72628–42. Available from: https://consensus.app/papers/multiagent-reinforcement-learning-strategic-decision-brand%C3%A3o/25dccc2dca775666ad2870a2e67417c0/

[22] Kober J, Bagnell J, Peters J. Reinforcement learning in robotics: A survey. Int J Robot Res [Internet]. 2013 [cited 2024 Mar 14];32:1238–74. Available from: https://consensus.app/papers/reinforcement-learning-robotics-survey-kober/ebedf07059a2557dbd163b0711a188b0/

[23] Haasdijk E, Bredeche N, Eiben AE. Combining Environment-Driven Adaptation and Task-Driven Optimisation in Evolutionary Robotics. PLOS ONE [Internet]. 2014 Jun 5 [cited 2024 Mar 14];9(6):e98466. Available from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0098466

[24] Cursi F, Bai W, Yeatman EM, Kormushev P. Task Accuracy Enhancement for a Surgical Macro-Micro Manipulator With Probabilistic Neural Networks and Uncertainty Minimization. IEEE Trans Autom Sci Eng [Internet]. 2024 Jan [cited 2024 Mar 14];21(1):241–56. Available from: https://ieeexplore.ieee.org/document/9945972

[25] Suroor N, Hussain I, Khalique A, Khan TA. Analyzing the Effects of Reinforcement Learning to Develop Humanoid Robots. Int J End-User Comput Dev IJEUCD [Internet]. 2019 [cited 2024 Mar 14];8(1):55–66. Available from: https://www.igi-global.com/gateway/article/www.igi-global.com/gateway/article/250877

[26] Penmetcha M, Kannan SS, Min BC. Smart Cloud: Scalable Cloud Robotic Architecture for Web-powered Multi-Robot Applications [Internet]. arXiv; 2020 [cited 2024 Mar 14]. Available from: http://arxiv.org/abs/1912.02927

[27] Zhao Y, Chi Y, Hong Y, Li Y, Yang S, Yin J. Twisting for soft intelligent autonomous robot in unstructured environments. Proc Natl Acad Sci [Internet]. 2022 May 31 [cited 2024 Mar 14];119(22):e2200265119. Available from: https://www.pnas.org/doi/10.1073/pnas.2200265119

[28] Luckcuck M, Farrell M, Dennis LA, Dixon C, Fisher M. Formal Specification and Verification of Autonomous Robotic Systems: A Survey. ACM Comput Surv [Internet]. 2019 Sep 13 [cited 2024 Mar 14];52(5):100:1-100:41. Available from: https://dl.acm.org/doi/10.1145/3342355

[29] Niloy MdAK, Shama A, Chakrabortty RK, Ryan MJ, Badal FR, Tasneem Z, et al. Critical Design and Control Issues of Indoor Autonomous Mobile Robots: A Review. IEEE Access [Internet]. 2021 [cited 2024 Mar 14];9:35338–70. Available from: https://ieeexplore.ieee.org/document/9363869

[30] Kohlbrecher S, Romay A, Stumpf A, Gupta A, von Stryk O, Bacim F, et al. Human-robot Teaming for Rescue Missions: Team ViGIR's Approach to the 2013 DARPA Robotics Challenge Trials. J Field Robot [Internet]. 2015 [cited 2024 Mar 14];32(3):352–77. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/rob.21558

[31] Tong R, Feng Y, Wang J, Wu Z, Tan M, Yu J. A Survey on Reinforcement Learning Methods in Bionic Underwater Robots. Biomimetics [Internet]. 2023 Jun [cited 2024 Mar 14];8(2):168. Available from: https://www.mdpi.com/2313-7673/8/2/168

[32] Geng M, Liu S, Wu Z. Sensor Fusion-Based Cooperative Trail Following for Autonomous Multi-Robot System. Sensors [Internet]. 2019 Jan [cited 2024 Mar 14];19(4):823. Available from: https://www.mdpi.com/1424-8220/19/4/823

[33] Otero I, Inmaculada Otero, Salgado JF, Jesús Salgado, Moscoso S, Silvia Moscoso. Cognitive reflection, cognitive intelligence, and cognitive abilities: A meta-analysis. Intelligence. 2022 Jan 1;90:101614–101614.

[34] Kahneman D, Tversky A. Higher Education from Cambridge University Press. Cambridge University Press; 2000 [cited 2024 Mar 14]. Choices, Values, and Frames. Available from: https://www.cambridge.org/highereducation/books/choices-values-and-frames/9E500B8A9AB4B7DFE81BFEFDAC55E57E

[35] Toplak ME, West RF, Stanovich KE. Assessing miserly information processing: An expansion of the Cognitive Reflection Test. Think Reason [Internet]. 2014 Apr 3 [cited 2024 Mar 14];20(2):147–68. Available from: https://doi.org/10.1080/13546783.2013.844729

[36] Stanovich KE, West RF. Individual differences in reasoning: Implications for the rationality debate? Behav Brain Sci [Internet]. 2000 Oct [cited 2024 Mar 14];23(5):645–65. Available from: https://www.cambridge.org/core/journals/behavioral-and-brain-sciences/article/abs/individual-differences-in-reasoning-implications-for-the-rationality-debate/2906AEF620B36C10018DD291F790BE97

[37] Pennycook G, Cheyne JA, Barr N, Koehler DJ, Fugelsang JA. The role of analytic thinking in moral judgements and values. Think Reason [Internet]. 2014 Apr 3 [cited 2024 Mar 14];20(2):188–214. Available from: https://doi.org/10.1080/13546783.2013.865000

[38] Shtulman A, McCallum K. Cognitive Reflection Predicts Science Understanding. Cogn Sci [Internet]. 2014 [cited 2024 Mar 14];36. Available from: https://consensus.app/papers/reflection-predicts-science-understanding-shtulman/eb43b7e00ed753eb8a11797f8e9ef0fd/

[39] Sloman SA. The empirical case for two systems of reasoning. Psychol Bull. 1996;119(1):3–22.

[40] Evans JSBT. In two minds: dual-process accounts of reasoning. Trends Cogn Sci [Internet]. 2003 Oct 1 [cited 2024 Mar 14];7(10):454–9. Available from: https://www.cell.com/trends/cognitive-sciences/abstract/S1364-6613(03)00225-0

[41] Toplak ME, West RF, Stanovich KE. The Cognitive Reflection Test as a predictor of performance on heuristics-and-biases tasks. Mem Cognit [Internet]. 2011 Oct 1 [cited 2024 Mar 14];39(7):1275–89. Available from: https://doi.org/10.3758/s13421-011-0104-1

[42] Finucane ML, Gullion CM. Developing a tool for measuring the decision-making competence of older adults. Psychol Aging. 2010;25(2):271–88.

[43] Asada M. Modeling Early Vocal Development Through Infant–Caregiver Interaction: A Review. IEEE Trans Cogn Dev Syst [Internet]. 2016 Jun [cited 2024 Mar 14];8(2):128–38. Available from: https://ieeexplore.ieee.org/document/7452400

[44] Sanchez-Lopez JL, Suarez Fernandez RA, Bavle H, Sampedro C, Molina M, Pestana J, et al. AEROSTACK: An architecture and open-source software framework for aerial robotics. In: 2016 International Conference on Unmanned Aircraft Systems (ICUAS) [Internet]. Arlington, VA: IEEE; 2016 [cited 2024 Mar 13]. p. 332–41. Available from: https://ieeexplore.ieee.org/document/7502591/

[45] Spatola N, Chaminade T. Precuneus brain response changes differently during human–robot and human–human dyadic social interaction. Sci Rep [Internet]. 2022 Aug 30 [cited 2024 Mar 13];12(1):14794. Available from: https://www.nature.com/articles/s41598-022-14207-9

[46] Chacón A, Ponsa P, Angulo C. Cognitive Interaction Analysis in Human–Robot Collaboration Using an Assembly Task. Electronics [Internet]. 2021 Jan [cited 2024 Mar 19];10(11):1317. Available from: https://www.mdpi.com/2079-9292/10/11/1317

[47] Chien SY, Lin YL, Lee PJ, Han S, Lewis M, Sycara K. Attention allocation for human multi-robot control: Cognitive analysis based on behavior data and hidden states. Int J Hum-Comput Stud [Internet]. 2018 Sep 1 [cited 2024 Mar 19];117:30–44. Available from: https://www.sciencedirect.com/science/article/pii/S107158191830096X

[48] Wang J, Yan R, Tang H. Multi-Scale Extension in an Entorhinal-Hippocampal Model for Cognitive Map Building. Front Neurorobotics [Internet]. 2021 Jan 14 [cited 2024 Mar 14];14. Available from: https://www.frontiersin.org/articles/10.3389/fnbot.2020.592057

[49] Tsagarakis NG, Metta G, Sandini G, Vernon D, Beira R, Becchi F, et al. iCub: the design and realization of an open humanoid platform for cognitive and neuroscience research. Adv Robot [Internet]. 2007 Jan 1 [cited 2024 Mar 14];21(10):1151–75. Available from: https://doi.org/10.1163/156855307781389419

[50] Bohg J, Kragic D. Learning Action-Perception Cycles in Robotics: A Question of Representations and Embodiment. In: Engel AK, Friston KJ, Kragic D, editors. The Pragmatic Turn: Toward Action-Oriented Views in Cognitive Science [Internet]. The MIT Press; 2016 [cited 2024 Mar 14]. p. 0. Available from: https://doi.org/10.7551/mitpress/9780262034326.003.0018

[51] Benjamin DP, Lonsdale D, Lyons D, Patel S. Using Cognitive Semantics to Integrate Perception and Motion in a Behavior-Based Robot. In: 2008 ECSIS Symposium on Learning and Adaptive Behaviors for Robotic Systems (LAB-RS) [Internet]. 2008 [cited 2024 Mar 14]. p. 77–82. Available from: https://ieeexplore.ieee.org/document/4599431

[52] Prescott TJ. Editorial. Connect Sci [Internet]. 2014 Jan 2 [cited 2024 Mar 14];26(1):1–4. Available from: https://doi.org/10.1080/09540091.2013.877219

[53] Pointeau G, Dominey PF. The Role of Autobiographical Memory in the Development of a Robot Self. Front Neurorobotics [Internet]. 2017 Jun 20 [cited 2024 Mar 14];11. Available from: https://www.frontiersin.org/articles/10.3389/fnbot.2017.00027

[54] Boucenna S, Cohen D, Meltzoff AN, Gaussier P, Chetouani M. Robots Learn to Recognize Individuals from Imitative Encounters with People and Avatars. Sci Rep [Internet]. 2016 Feb 4 [cited 2024 Mar 14];6(1):19908. Available from: https://www.nature.com/articles/srep19908

[55] McColl D, Nejat G. Meal-time with a socially assistive robot and older adults at a long-term care facility. J Hum-Robot Interact [Internet]. 2013 Feb 27 [cited 2024 Mar 14];2(1):152–71. Available from: https://dl.acm.org/doi/10.5898/JHRI.2.1.McColl

[56] Phan HP, Ngu BH, Yeung AS. Achieving Optimal Best: Instructional Efficiency and the Use of Cognitive Load Theory in Mathematical Problem Solving. Educ Psychol Rev [Internet]. 2017 Dec 1 [cited 2024 Mar 14];29(4):667–92. Available from: https://doi.org/10.1007/s10648-016-9373-3

[57] Cross ES, Ramsey R. Mind Meets Machine: Towards a Cognitive Science of Human–Machine Interactions. Trends Cogn Sci [Internet]. 2021 Mar 1 [cited 2024 Mar 14];25(3):200–12. Available from: https://www.cell.com/trends/cognitive-sciences/abstract/S1364-6613(20)30297-7

[58] Binney RJ, Ramsey R. Social Semantics: The role of conceptual knowledge and cognitive control in a neurobiological model of the social brain. Neurosci Biobehav Rev [Internet]. 2020 May 1 [cited 2024 Mar 14];112:28–38. Available from: https://www.sciencedirect.com/science/article/pii/S0149763419301915

[59] Moerland TM, Broekens J, Jonker CM. Emotion in reinforcement learning agents and robots: a survey. Mach Learn [Internet]. 2018 Feb 1 [cited 2024 Mar 14];107(2):443–80. Available from: https://doi.org/10.1007/s10994-017-5666-0

[60] Dautenhahn K. Socially intelligent robots: dimensions of human–robot interaction. Philos Trans R Soc B Biol Sci [Internet]. 2007 Feb 13 [cited 2024 Mar 14];362(1480):679–704. Available from: https://royalsocietypublishing.org/doi/10.1098/rstb.2006.2004

[61] Asada M. Development of artificial empathy. Neurosci Res [Internet]. 2015 Jan 1 [cited 2024 Mar 14];90:41–50. Available from: https://www.sciencedirect.com/science/article/pii/S0168010214003186

[62] Frohnwieser A, Murray JC, Pike TW, Wilkinson A. Using robots to understand animal cognition. J Exp Anal Behav [Internet]. 2016 [cited 2024 Mar 14];105(1):14–22. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/jeab.193

[63] Heinen MR, Engel PM. Evaluation of visual attention models under 2D similarity transformations. In: Proceedings of the 2009 ACM symposium on Applied Computing [Internet]. New York, NY, USA: Association for Computing Machinery; 2009 [cited 2024 Mar 14]. p. 1156–60. (SAC '09). Available from: https://doi.org/10.1145/1529282.1529539

[64] Changjiu Z, Qingchun M, Zhongwen G, Wiefen Q, Bo Y. Incorporation of perception-based information in robot learning using fuzzy reinforcement learning agents. J Ocean Univ Qingdao [Internet]. 2002 Apr 1 [cited 2024 Mar 14];1(1):93–100. Available from: https://doi.org/10.1007/s11802-002-0038-0

[65] Baheri A, Nageshrao S, Tseng HE, Kolmanovsky I, Girard A, Filev D. Deep Reinforcement Learning with Enhanced Safety for Autonomous Highway Driving [Internet]. arXiv; 2020 [cited 2024 Mar 14]. Available from: http://arxiv.org/abs/1910.12905

[66] Liu J, Liu P, Feng L, Wu W, Lan H. Automated Clash Resolution of Rebar Design in RC Joints using Multi-Agent Reinforcement Learning and BIM. ISARC Proc [Internet]. 2019 May 24 [cited 2024 Mar 14];921–8. Available from: http://www.iaarc.org/publications/2019_proceedings_of_the_36th_isarc/automated_clash_resolution_of_rebar_design_in_rc_joints_using_multi_agent_reinforcement_learning_and_bim.html

[67] Steinke A, Lange F, Kopp B. Parallel model-based and model-free reinforcement learning for card sorting performance. Sci Rep [Internet]. 2020 Sep 22 [cited 2024 Mar 14];10(1):15464. Available from: https://www.nature.com/articles/s41598-020-72407-7

[68] Mayer MPh, Odenthal B, Faber M, Neuhöfer J, Kabuß W, Kausch B, et al. Cognitive Engineering for Direct Human-Robot Cooperation in Self-optimizing Assembly Cells. In: Kurosu M, editor. Human Centered Design. Berlin, Heidelberg: Springer; 2009. p. 1003–12.

[69] Ismail LI, Hanapiah FA, Belpaeme T, Dambre J, Wyffels F. Analysis of Attention in Child–Robot Interaction Among Children Diagnosed with Cognitive Impairment. Int J Soc Robot [Internet]. 2021 Apr 1 [cited 2024 Mar 14];13(2):141–52. Available from: https://doi.org/10.1007/s12369-020-00628-x

[70] Papadopoulos GT, Antona M, Stephanidis C. Towards open and expandable cognitive AI architectures for large-scale multi-agent human-robot collaborative learning [Internet]. arXiv; 2021 [cited 2024 Mar 14]. Available from: http://arxiv.org/abs/2012.08174

[71] Scheutz M. The Case for Explicit Ethical Agents. AI Mag [Internet]. 2017 [cited 2024 Mar 14];38(4):57–64. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1609/aimag.v38i4.2746

[72] Shah TR, Kautish P, Mehmood K. Influence of robots service quality on customers' acceptance in restaurants. Asia Pac J Mark Logist [Internet]. 2023 Jan 1 [cited 2024 Mar 14];35(12):3117–37. Available from: https://doi.org/10.1108/APJML-09-2022-0780

[73] Cangelosi A, Schlesinger M. From Babies to Robots: The Contribution of Developmental Robotics to Developmental Psychology. Child Dev Perspect [Internet]. 2018 [cited 2024 Mar 14];12(3):183–8. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1111/cdep.12282

[74] Damiano L, Dumouchel P. Anthropomorphism in Human–Robot Co-evolution. Front Psychol [Internet]. 2018 Mar 26 [cited 2024 Mar 14];9. Available from: https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2018.00468/full

[75] Mahmood S, Ampadu KO, Antonopoulos K, Panagiotou C, Mendez SAP, Podlubne A, et al. Prospects of Robots in Assisted Living Environment. Electronics [Internet]. 2021 Jan [cited 2024 Mar 14];10(17):2062. Available from: https://www.mdpi.com/2079-9292/10/17/2062

[76] Di Nuovo A, Varrasi S, Lucas A, Conti D, McNamara J, Soranzo A. Assessment of Cognitive skills via Human-robot Interaction and Cloud Computing. J Bionic Eng [Internet]. 2019 May 1 [cited 2024 Mar 14];16(3):526–39. Available from: https://doi.org/10.1007/s42235-019-0043-2

[77] Lanillos P, Ferreira JF, Dias J. Designing an artificial attention system for social robots. In: 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) [Internet]. 2015 [cited 2024 Mar 14]. p. 4171–8. Available from: https://ieeexplore.ieee.org/document/7353967

[78] Nakamura T, Nagai T, Taniguchi T. SERKET: An Architecture for Connecting Stochastic Models to Realize a Large-Scale Cognitive Model. Front Neurorobotics [Internet]. 2018 Jun 26 [cited 2024 Mar 14];12. Available from: https://www.frontiersin.org/articles/10.3389/fnbot.2018.00025

[79] Tikhanoff V, Cangelosi A, Metta G. Integration of Speech and Action in Humanoid Robots: iCub Simulation Experiments. IEEE Trans Auton Ment Dev [Internet]. 2011 Mar [cited 2024 Mar 14];3(1):17–29. Available from: https://ieeexplore.ieee.org/document/5672581

[80] Ryan M, van der Burg S, Bogaardt MJ. Identifying key ethical debates for autonomous robots in agri-food: a research agenda. AI Ethics [Internet]. 2022 Aug 1 [cited 2024 Mar 14];2(3):493–507. Available from: https://doi.org/10.1007/s43681-021-00104-w

[81] Manzotti R, Chella A. Good Old-Fashioned Artificial Consciousness and the Intermediate Level Fallacy. Front Robot AI [Internet]. 2018 Apr 18 [cited 2024 Mar 14];5. Available from: https://www.frontiersin.org/articles/10.3389/frobt.2018.00039

[82] Salas-Pilco SZ. The impact of AI and robotics on physical, social-emotional and intellectual learning outcomes: An integrated analytical framework. Br J Educ Technol [Internet]. 2020 [cited 2024 Mar 14];51(5):1808–25. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1111/bjet.12984

[83] Szczepanowski R, Gakis M, Sobecki KA and J, Szczepanowski R, Gakis M, Sobecki KA and J. Computational Models of Consciousness-Emotion Interactions in Social Robotics: Conceptual Framework. In: Cognitive and Computational Neuroscience - Principles, Algorithms and Applications [Internet]. IntechOpen; 2017 [cited 2024 Mar 14]. Available from: https://www.intechopen.com/chapters/58175

[84] Gutiérrez SM, Steinbauer-Wagner G. The Need for a Meta-Architecture for Robot Autonomy. Electron Proc Theor Comput Sci [Internet]. 2022 Jul 20 [cited 2024 Mar 14];362:81–97. Available from: http://arxiv.org/abs/2207.09712

[85] Alvarez L, Wiebe SA, Adams K, Hope A, Cook A. The neurophysiology of augmentative manipulation: A method for technical implementation. Technol Disabil [Internet]. 2014 Jan 1 [cited 2024 Mar 14];26(2–3):65–77. Available from: https://content.iospress.com/articles/technology-and-disability/tad00410