Expanding the Scope — Cognitive Robotics Meets NeuroIS

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Abstract Cognitive Robotics aims to develop robots that can perform tasks, learn from experiences, and adapt to new situations using cognitive skills. Rooted in neuroscience theories, Cognitive Robotics provides a unique opportunity for NeuroIS researchers to theorize and imagine intelligent autonomous agents as natural cognitive systems. By translating Cognitive Robotics methods and architectures into the NeuroIS into the 2 × 2 design science research matrix, we intend to help researchers gain deeper insights into how humans perceive and interact with their environment. These insights may not only improve cognitive architectures but may also enable a better design and evaluation of user-centric NeuroIS systems, safer test propositions, and better self-adaptable systems that can effectively collaborate with humans in various settings.

Keywords Cognitive robotics · NeuroIS · Cross-fertilization · Design science research · Cognitive architecture

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1 Introduction

NeuroIS has proven its value as a bridge between neuroscience, psychology, and information systems research to study the impact of new technology and its use. The data obtained from the research process can also inform new designs and applications of information systems [1]. NeuroIS researchers typically use self-reporting data to explore the effects of technology use in addition to neuroimaging techniques such as EEG, fMRI, and eye tracking to collect data on brain activity while participants interact with technology [2]. This helps them gain richer insights into how users perceive and process information, make decisions, and experience emotions when using technology. Results of these analyses often deliver objectives or requirements that can be used to improve or design information systems focused on the user [3, 4].

Since NeuroIS research heavily draws on neurophysiological data to test hypotheses, a substantial number of participants is required for each experiment [1, 5]. However, it is often difficult to find the required number of participants that meet sampling criteria [6]. At the same time, neurophysiological methods require a joint analysis of environmental stimuli, the neural system, and bodily reactions, which is why virtual models cannot easily replace participants. Recent advances in cognitive neuroscience, however, may push this boundary. Gravish and Lauder [7], for instance, elaborated on using robots as surrogates to study behavior and cognition in a controlled environment. Considering robots as a model of the living system under investigation results in exploring an often isolated albeit very concrete (behavioral) variable [7]. Testing such variables in vivo and in a natural environment is challenging. Thus, using robots as a model of the living system under investigation enables researchers to make inferences about the living system that would otherwise have been difficult to obtain [8]. At the same time, robot-supported social cognitive neuroscience (rSCN) uses robots as a new type of stimuli to study cognition and behavior in humans and animals in a highly controlled experimental setting [9].

Although these more technical advancements in neuroscience already provide promising avenues of research for NeuroIS, another emerging field in robotics may push the boundaries even further. Cognitive Robotics (CogRob) uses innovation in robotics, artificial intelligence, and cognitive science to design robots that can perform complex tasks autonomously and adapt to changing environments [10]. These robots can be used in various settings, such as manufacturing, healthcare care [11], and space exploration [12]. They often help improve efficiency and reduce costs [13].

CogRob typically combines neuroscience and engineering with other disciplines, such as psychology and social sciences. This elevates robots beyond their use as simple tools or models. Robots can become platforms that help researchers explore complex cognitive issues in human-technology interaction in various social contexts [14]. Moreover, insights from CogRob can benefit the development of more powerful learning algorithms that enable the study of controlled variables in isolation providing new angles for research in psychology and neuroscience. CogRob also allows for the development of more robust robots to effectively collaborate with humans [8, 14, 15]. To better leverage the advancements in CogRob for NeuroIS, we propose CogRob methods as integral elements of the NeuroIS Design Science Cycle (DSC). We specifically aim to investigate how integrating CogRob methods and models into the NeuroIS DSC can help develop more user-centric information systems. In the following sections, we will explore the background of CogRob, its foundation, the respective methods, and how CogRob can help create better experimental settings for NeuroIS research and aid the design of user-centric information systems within the DSC.

2 Cognitive Robotics as an Emerging Field

Cognitive Robotics is an interdisciplinary field that aims to develop robots that can perform tasks, adapt to new situations [16], and learn from experiences to create machines inspired by how humans think and learn [10]. CogRob uses cognitive skills such as memory, decision-making, action understanding, and prediction but also combines ideas from other fields, such as computer science, robotics, artificial intelligence, psychology, neuroscience, and philosophy. The intention of CogRob is not to replace but to efficiently learn from problem-solving human interactions [17].

Relevant architectures and models at the intersection of neuroscience and robotics were built on the initial memory theory that surrounds, for example, the Simon and Feigenbaum architecture for cognition. The EPAM model [18] includes learnings from human memory and speech development. Later Anderson, who researched human memory, proposed the Human Associative Memory (HAM) model [19], which his student Bower further developed into the ACT model [20]. ACT-R is a cognitive architecture that aims to explain how humans perform tasks, learn new skills, and solve problems, including aspects of long-term memory and thinking processes.

Researchers use architectures and models to develop robots that can learn and reason like humans. This may help them gain insights into how humans process information, interact with their environment, and adapt to new situations [21, 22]. It can also improve the general understanding of human cognition and behavior, which may provide the foundation for the development of new therapies and interventions for persons with cognitive impairments or disabilities neuroscience [22],

The theoretical foundations of CogRob are based on learning theories such as reinforcement learning, unsupervised learning, and imitation learning [23]. Many methods and approaches used in CogRob are known from artificial intelligence machine learning and natural language processing research. The main models and architectures in CogRob include behavior-based robotics, hybrid architectures, and cognitive architectures [24], which are commonly symbolic, connectionist, or hybrid [25]. The architectures typically follow a bottom-up approach in which basic rules or nodes generate complex behavior. This differs from common AI approaches, in which a top-down process created by the programmer inspires behavior [26]. More specifically, CogRob builds on the assumption that the mind has various modular cognitive units, each responsible for a specific aspect of human cognition [20]. These interconnected modules work together to generate intelligent behavior [27]. Anderson's work [20], "The Architecture of Cognition," is considered a landmark in this context. Kotseruba and Tsotsos [24] build on his work and say that combining psychology and computer science insights inspired the first cognitive architectures, while theoretical models of human cognitive processes and related software artifacts inspired CogRob.

3 Generalizing the Cognitive Robotics Approach

In Cognitive Robotics, robots typically undergo a cognitive cycle similar to that of humans. This cycle starts with sensing the environment through sensors, interpreting the data received during the perceptual process, making decisions based on internal needs, possible actions, outcomes, emotions, motivations, and context, and acting in the environment. Figure 1 illustrates a basic cognitive cycle with possible submodules for each component of cognition.

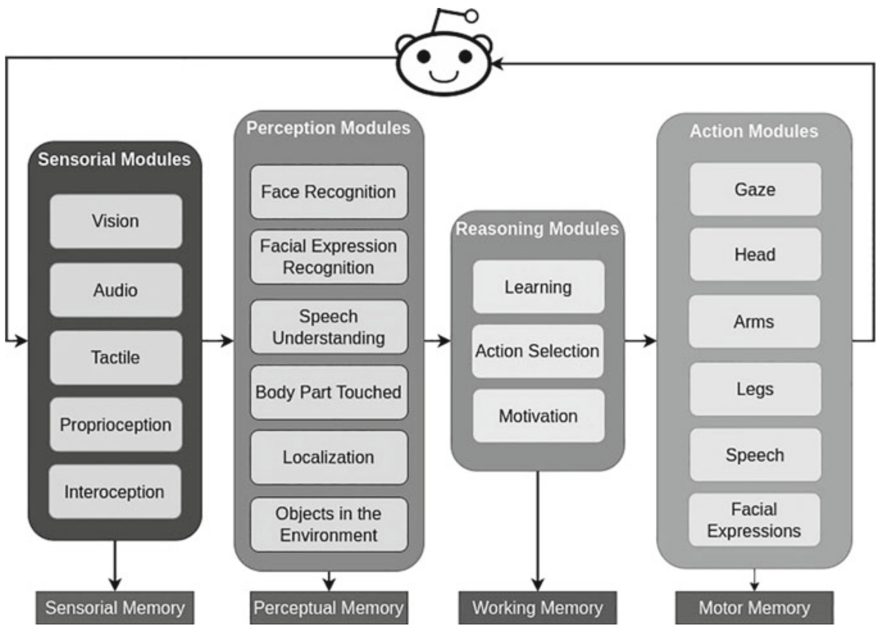

Fig. 1 Basic cognitive cycle used in a cognitive architecture. The submodules in each module are examples of possible components the robot can use. Each developer can choose which one to use and how to implement it

All modules can run in parallel according to their specificity. This allows each module to be modeled individually and then connected to the system, which is particularly valuable for exploring the impact of one module in the application without changing the entire cognitive architecture. Isolating the modules makes it possible to work in one specific module and observe the agent's behavior with certain changes. This enables accurate comparisons between approaches while maintaining the cognitive process. The work in Berto et al. [28], and strategies a simulated autonomous agent learned using two motivational mechanisms as part of the cognitive architecture. In this way, researchers could investigate and compare the impact of different elements, such as needs and pleasure, during the decision-making process under the same conditions.

4 Cognitive Robotics and the NeuroIS Design Science Cycle

Potential cross-fertilization between neuroscience and Cognitive Robotics particularly focused on how CogRob benefits from neuroscience theories and tools can advance and improve robot functions. In addition, CogRob methods and architectures can create artificial experimental settings to test variables in isolation [8]. To better incorporate the potential of CogRob methods and architectures for NeuroIS, we build on the proposed 2×2 matrix by vom Brocke and colleagues [4]. The model establishes how neuroscience theories and tools can help improve the design and evaluation of information systems within the DSR cycle. We expand this 2×2 by a $2 \times 2(+2)$ matrix, positioning CogRob methods and architectures as a valuable addition to designing and improving user-centric information systems (Fig. 2).

The expanded framework aims to demonstrate that CogRob can benefit NeuroIS design science research by complementing the theories and tools of neuroscience through computerized modeling. This capability expands the previously proposed three neuroscience application strategies in IS design science research by a CogRob dimension. The tentative application strategies for CogRob complement NeuroIS design science research as follows.

Strategy 1: *Use of neuroscience theories and cognitive robotic methods to build and evaluate user-centric IT artifacts.*

A study by Baima and Luna Colombini [29] showed that a robot could learn object affordances by interacting only with tactile sensors, thus simulating how blind users learn to interact with an unknown artifact. However, the architecture's adaptability allows the sensor type to change from tactile to vision or to have both as input, enabling the isolation of the evaluation and building of the IT artifact considering different scenarios. Such an approach would allow researchers to study variables more in-depth and use this knowledge to improve the design of artifacts regarding user-friendliness, productivity, and user experience.

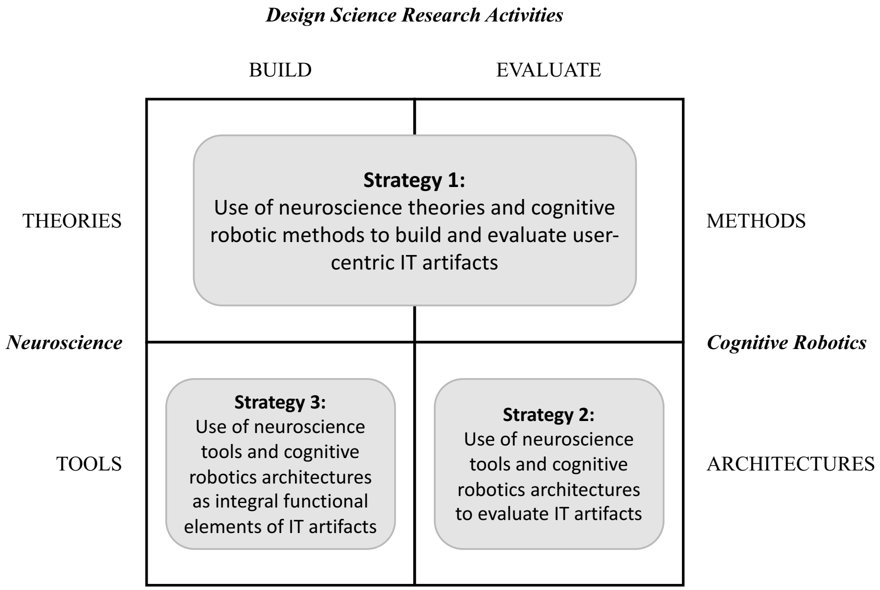

Fig. 2 The expanded NeuroIS Design Science Research Framework by CogRob methods and models for novel approaches to building and evaluating information systems (adapted from Brocke et al. [4])

Strategy 2: *Use of neuroscience tools and cognitive robotics architectures to evaluate IT artifacts.*

Researchers can isolate specific modules of an agent and observe its behavior under different conditions to make accurate comparisons between approaches. Researchers, for instance, can investigate the impact of two motivational mechanisms—e.g., needs and pleasure—on a simulated autonomous agent's decision-making behavior as part of its cognitive architecture [28]. This approach allows for the simulated isolation of the users' emotions in behavioral responses while interacting with applications and artifacts. Results can inform the redesign of the artifact in the simulation before the improved artifact is tested with the participants.

Strategy 3: *Use of neuroscience tools and cognitive robotics architectures as integral functional elements of IT artifacts.*

Incorporating cognitive architectural modules into chatbots, such as chatGPT [30], can enable self-adjustment and rebalancing of cognitive modules based on user feedback, either predicted (sentiment analysis) or user informed (through a "like"-button), allowing for the testing of new ideas in business models and their impact on user acceptance and trust. For instance, a study using this CogRob module demonstrated interactional justice's impact on the service recovery [31]. This approach allows NeuroIS researchers to create new paradigms and test human responses to behaviors while interacting with humans or other robots through IT artifacts.

5 Discussion

As an emerging field, Cognitive Robotics provides many interesting impulses for NeuroIS. Current benefits range from creating specific testing environments and testing variables in isolation to assessing user behavior and improving system designs based on user behavior. Moreover, machine learning algorithms in CogRob, combined with CogRob architectures and models, may help develop more practical models for brain-computer interactions. This interplay can adjust a user interface in near real-time, which may improve attitudes, performance, productivity, and well-being.

Despite the potential benefits of CogRob, it is challenging to integrate this emerging field into NeuroIS research and design. As an emerging field, CogRob requires a more explicit framework and definition to differentiate its approach from common machine learning and artificial intelligence frameworks [21, 32]. In particular, the term 'learning' is often used in the context of machine learning, which can be misleading regarding the true abilities of what machines are learning. It also needs to be more evident where CogRob can be used and to what extent. When it comes to, for instance, the testing of variables in a CogRob environment instead of an experiment with human participants, the current hardware limitations should be considered. Computers reach up to 500 processing cores, while the human brain processes information on billions of neurons in parallel. The result may not quickly transfer to the human organism [33].

6 Conclusion

NeuroIS and Cognitive Robotics are rapidly growing and interdisciplinary fields. Combined, they may significantly enhance our understanding of human behavior and intelligent systems. Building on vom Brocke and colleagues' work [4], we expand the 2×2 matrix on integrating neurobiology into the design science research cycle by CogRob methods and architectures. While preparing the $2 \times 2(+2)$ matrix, we introduce possible application areas at the intersection of CogRob and NeuroIS, highlighting how each discipline can cross-fertilize. Overall, cross-fertilization can lead to more effective and user-friendly cognitive architectures, aligning IT artifacts with users' perceptual and information-processing mechanisms, ultimately improving agent behaviors.

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