# Towards Intelligent Adaption in Cognitive Assistance Systems through Physiological Computing

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## Abstract

With the growing prevalence of cognitive impairments around the globe and in Europe, an increasing number of people are likely to experience cognitive decline during their working years. Supporting these individuals to remain in employment is imperative, both to promote personal well-being and to enable organizations to retain experienced and skilled workers. This research proposes the design of a physiologically adaptive cognitive assistance system to support individuals with mild cognitive impairment in sheltered workshops. This work adopts a design science research approach, combining laboratory and field experiments to achieve user-centred design. Expected outcomes include a modular framework for physiologically adaptive cognitive assistive systems, a multimodal machine learning pipeline for detecting psychological states from physiological signals and design principles to inform future research and development. By demonstrating the potential of such systems within work settings, this research aims to advance the social inclusion of individuals with mild cognitive impairment in the labour market.

## CCS Concepts

• **Human-centered computing** → **Human computer interaction (HCI)**; *User centered design*; • **Computing methodologies** → **Machine learning**; • **Hardware** → **Sensor applications and deployments**; • **Applied computing** → *Psychology*; • **Social and professional topics** → *People with disabilities.*

## Keywords

mild cognitive impairment; cognitive assistance system; human–robot interaction; physiological computing

**ACM Reference Format:**
Jordan Schneider. 2025. Towards Intelligent Adaption in Cognitive Assistance Systems through Physiological Computing. In *Proceedings of the 27th International Conference on Multimodal Interaction (ICMI '25), October 13–17, 2025, Canberra, ACT, Australia.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3716553.3750828


*ICMI '25, Canberra, ACT, Australia*

ACM ISBN 979-8-4007-1499-3/2025/10
https://doi.org/10.1145/3716553.3750828

## 1 Introduction

Cognitive impairments are the loss of various cognitive functions, such as attention, memory and language, and can be diagnosed as dementia if the decline is severe enough to prevent independence in daily activities [18]. The prevalence of mild cognitive impairment (MCI) has been found to be 21.2 % globally and 19.7 % in Europe and Central Asia [10], with the Organisation for Economic Co-operation and Development reporting that the number of people over 60 years of age living with dementia in the European Union could rise to 13.4 million in 2030 [25]. Not only does the condition significantly impact the quality of life of the affected individuals, but the associated care costs also imposes a considerable economic burden to society [34].

Some individuals will develop cognitive impairments during their working years, which can translate into forgetting information or difficulties staying focused and keeping up with tasks [38]. Supporting people with MCI to remain in employment benefits organizations through the retention of experienced staff, whilst also promoting these workers' quality of life, well-being and social inclusion [32]. In particular, assistance systems have the potential to promote equitable participation in the workforce for individuals with cognitive impairments by addressing barriers to task performance [4]. For instance, in sheltered-workshop trials a collaborative robot offering assistance in the form of pointing gestures has been shown to significantly boost performance on assembly tasks and to accelerate task learning [13, 14]. Similarly, social robots that can engage users through natural and intuitive communication modes have seen some success in special education [26].

In order to be effective, socially assistive robots must be capable of recognizing human internal states and responding to these appropriately [35]. This can be achieved through the integration of physiological signals measured from sensors worn on the user into a cybernetic loop in which a computer system adapts its behaviour based on the psychological states inferred from those measurements [19]. Roy et al. [28] lay out a general framework for the application of physiological computing in human–robot interaction (HRI), but the authors also draw attention to the technical challenges in transferring classifiers trained on offline data in the laboratory to a real-time online context in the field as well as the need to develop suitable planning algorithms that make use of the classifier outputs. This could explain the current lack of guidance and examples for researchers wanting to develop such systems to be deployed in real-world settings.

Hence, this project proposes the design of a physiologically adaptive cognitive assistance system to support workers during assembly tasks in sheltered workshops. It also aims to explore how multiple physiological signals can be combined to estimate cognitive workload and how assistance systems can act on this information to intelligently adapt their own behaviour. This will serve as a reusable foundation for future research to build upon.

Throughout the project, the following research questions will be investigated:

(1) Which task contexts in sheltered workshops offer the greatest opportunity for a cognitive assistance system to support workers with MCI?
(2) What functional and non-functional requirements must this system meet to address the user needs and challenges?
(3) How can cognitive workload be estimated robustly from multimodal physiological signals under real-time constraints?
(4) How can a modular framework be built to facilitate physiological adaptation in cognitive assistance systems?
(5) In which task contexts do workers with MCI find different assistance strategies most helpful?
(6) What insights can be gained to inform the design of future physiologically adaptive cognitive assistance systems?

## 2 Related Work

Over the past few decades, there has been a growing interest in taking advantage of physiological signals, such as electrocardiography (ECG), electroencephalography (EEG), electrodermal activity (EDA), photoplethysmography (PPG) or heart rate (HR), to estimate mental states during human–computer interaction (HCI) [2]. This process, known as psychophysiological inference, is based on the assumption that there exists a mapping of psychological states onto one or more physiological states [8]. After feeding the predictions from a psychophysiological inference algorithm into a system, it can then adapt to changes to the user's mental states in real time, thereby forming a so-called biocybernetic loop [31]. Such systems can be described as physiologically adaptive.

In the field of affective computing, psychophysiological inference has certain advantages over other methods for emotion recognition in that physiological signals are produced continuously and subconsciously, making it harder to intentionally manipulate them. For instance, Saffaryazdi et al. [29] showed how physiological signals, such as EEG, EDA and PPG, can be combined with behavioural responses like facial micro-expressions to identify emotions and noted that, similar to physiological signals, these micro-expressions are involuntary responses to external stimuli and are more reliable in comparison to macro-expressions. In another study, Darzi and Novak [11] explored emotion recognition for task adaption by estimating the enjoyment, valence, arousal and perceived difficulty of participants whilst playing a Pong-like video game from the physiological linkage between the two players using electromyography (EMG), ECG, EDA, respiration (RSP) and performance data.

Other psychological states that have been studied for HCI include engagement, stress and cognitive load. The first of these was the focus of a study by Perugia et al. [27], which used EEG and eye tracking data to measure the engagement of children with autism spectrum disorder (ASD) during a robot-assisted language intervention. Other studies examined stress levels of participants in diverse settings, such as detecting stressful conversations, forecasting mood as well as health and stress [3, 16, 21, 39]. The physiological signals used in these studies were ECG, EDA, PPG, RSP, skin temperature (SKT) and inter-beat interval (IBI), extracted from wearables, touch screens and wirelessly transmitted radio waves reflected from the body. Similarly, Novak et al. [24] and Aygun et al. [1] looked at estimating the cognitive load of the user during HRI with different machine learning algorithms using eye tracking in combination with various physiological signals, such as blood pressure (BP), RSP, SKT, EDA, ECG and EEG. Lastly, Mauri et al. [23] investigated the reliability of various physiological signals to predict multiple affective states, including relaxation, engagement and stress, and found that skin conductance and respiration were the best at differentiating the three states.

Cognitive workload is of particular relevance to this work. According to the Theory of Cognitive Load [33], human working memory has a limited capacity and cognitive performance is reduced when this is exceeded. This has also been confirmed experimentally in work environments by Biondi et al. [6], who showed that increased cognitive demand induced through an n-back task resulted not only in reduced performance but also higher muscle activity and self-reported workload during a concurrently executed assembly task. Although there are subjective measures for determining cognitive workload, including the NASA Task Load Index (NASA) or Subjective Workload Assessment Technique (SWAT), statistical or machine-learning approaches that use physiological and behavioural signals, such as EEG, ECG, functional magnetic response imaging (fMRI) and functional near-infrared spectroscopy (fNIR) and eye tracking, allow for monitoring cognitive workload in real-time [12].

Through providing appropriate assistance, an intelligent agent can help regulate cognitive workload and, thus, increase task performance. In their study, Brachten et al. [7] showed that users who could ask a virtual assistant for help while solving a difficult problem had a lower overall cognitive workload than the control group. Collaborative robots have also been investigated for cognitive workload reduction, but Landi et al. [20] found that physical assistance alone does not necessarily reduce perceived mental strain unless the system monitors the operator's state to provide support only when it is actually required. Indeed, Cavicchi et al. [9] argue that a human-like robot can serve as a cognitive offloading tool through social interaction. Beyrodt et al. [5], for instance, showed how a socially interactive agent can promote flow experiences during workplace tasks through interventions aimed at emotional regulation. This builds a compelling case for further research into cognitive assistance systems that are aware of human internal states for task support in work environments.

## 3 Proposed Work

As a methodological framework, the design science research (DSR) paradigm [15] provides a solid foundation for the research project. Whilst originally intended to be applied to architectural design, it has since also seen increasing use in information systems [17]. In their paper, van Turnhout et al. [36] identified several common

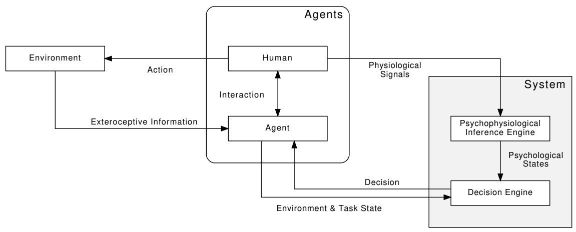


**Figure 1: System architecture**

design patterns in the literature by analysing the mixed methods used by HCI researchers according to the development oriented triangulation (DOT) framework, which categorizes research activities in HCI based on DSR [37]. One of these, which the authors call the rigour cycle, is especially applicable to this research.

This design pattern takes place over three phrases. During the first phase, FIND, an extensive literature review is to be conducted to discover prior work that can be built upon and possible improvements to the existing solutions. This will inform the second phase, INVENT, which focuses primarily on the development of the proposed cognitive assistance system. In the final phase, POSITION, the resulting prototype will be propositioned in the context of existing work as part of the dissertation.

A potential system architecture, based on the concept of the biocybernetic loop, is shown in Fig. 1. As the user completes an assembly task, wearable sensors measure physiological signals and an inference pipeline predicts the level of cognitive workload. This prediction is then fed to the decision engine, which uses this information to determine when and what assistive behaviours should be performed, such as offering to review instructions, reminding the user to take a break or calling the supervisors for additional help. These actions will then be executed by an intelligent agent. For performance reasons, the inference engine and decision engine will be run on an external computing unit and the Robot Operating System (ROS) 2 framework will be used for communication between the components. The closed-loop feedback should regulate the user's cognitive workload to improve performance and reduce errors.

As part of the *Zentrum Assistive Technologien Rhein-Ruhr* project in which this research is conducted, we are designing a reference architecture for pro-adaptive cognitive assistance systems. The reference architecture identifies and defines the relevant components and their interconnections such that it can inform and guide implementations in assistive technologies, thus enabling reuse and extension of components between scenarios. The proposed system architecture in Fig. 1 involves a scenario to support individuals with MCI in sheltered workshops and will include selected components from the reference architecture that are relevant to the scenario.

One of these components is an interactive reinforcement-learning framework that enables intelligent agents to learn an appropriate policy to adapt their responses based on signals provided by the user. This component will be used for the inference-to-action-loop in Figure 1, after adapting the state and action space as well as the feedback from the environment based on the results of Study 3. For evaluation, a basic rule-based decision engine can be used as a baseline.

The decision regarding which physiological sensors and modalities to use as part of the biocybernetic loop will be made in consultation with the experts at the sheltered workshop in which the system will be deployed, taking into consideration the results of Study 1. The intelligent agent could be a telepresence robot, but the exact choice of the robotic platform will similarly be discussed with the sheltered workshop upon completion of Study 3.

## 3.1 Planned Studies

*3.1.1 Study 1: Contextual Inquiry.* To ensure that the system design is grounded in the needs of the intended users, Study 1 undertakes a contextual inquiry in sheltered-workshop settings. During the experiment, staff and workers with MCI will be interviewed and observations made during routine assembly tasks, documenting both functional and non-functional requirements. The resulting thematic analysis will help to answer research questions 1 and 2.

*3.1.2 Study 2: Multimodal Psychophysiological Inference.* In Study 2, a list of candidate machine-learning models for inferring cognitive workload from physiological signals will be gathered based on existing systems in the literature. Selected models will then be trained on publicly available datasets and integrated into a multimodal fusion engine, which will later be evaluated against unimodal baseline classifiers in a simulated scenario. This study directly relates to research question 3.

*3.1.3 Study 3: Wizard-of-Oz Experiment.* Before full automation, Study 3 will employ a Wizard-of-Oz experiment to investigate user preferences for adaptive support strategies. Participants will perform assembly tasks while a hidden operator triggers predetermined prompts. Both quantitative metrics and qualitative feedback will be collected and used to determine which strategies are most effective. This study aligns with research question 5.

*3.1.4 Study 4: In-Situ Deployment.* Finally, Study 4 intends to validate the final prototype in an actual sheltered-workshop environment. During deployment, metrics, surveys and observational logs will be collected from a workshop station to evaluate task performance and user experiences. Thematic analysis will be employed to extract transferable design principles from the qualitative data. This study aims to address research question 6.

## 3.2 Current Work

The following tasks have been completed or are in progress:

- Compiled candidate machine-learning models and publicly available datasets for real-time inference of stress and cognitive workload.
- Presented and published a mini-paper on explainability methods for physio-behavioural time-series classification at the UbiComp/ISWC 2024 conference [30].
- Implemented an event-based fusion algorithm, building on the work by Lingenfelser et al. [22], that demonstrates the feasibility of integrating physiological data streams from heterogeneous sensors asynchronously.
- Established connections with a sheltered workshop within Germany to gain participant access and deployment space for the contextual inquiry (Study 1), wizard-of-oz experiment (Study 3) and in-situ evaluation (Study 4).

- Preparing a review of physiological computing in assistance systems to frame the project's theoretical contributions and guide the methodological design.
- Developing a proof-of-concept of the assistance system to be improved upon iteratively based on the insights gained from the proposed studies.

### 3.3 Remaining Work

The next step is to create the experimental protocol for the contextual inquiry (Study 1), which will inform design requirements and guide subsequent studies. This is then to be followed by implementing the multimodal fusion engine (Study 2), assessing support strategies (Study 3), developing the system prototype and validating it in situ (Study 4). The research outputs from each stage will be disseminated through scholarly publications, contributing to both the theoretical understanding and the practical development of physiologically adaptive cognitive assistance systems.

## 4 Research Contributions

This research will provide the following contributions:

**Modular Framework** Framework for integrating multimodal physiological signals to enable adaptive robot behaviour in cognitive assistance scenarios.

**Data Fusion Engine** Machine-learning pipeline for robustly fusing physiological signals from heterogeneous sensors together to infer human internal states.

**Empirical Insights** Practical insights into deploying assistive robots in real-world workplace settings, highlighting user needs and preferences regarding adaptive strategies.

**Open-Source Tools** Selected components of the prototype system will be released under an open-source licence to support reuse in other projects.

**Design Documentation** Learnings from the iterative development process will be synthesized into design patterns and guidelines for building physiologically adaptive cognitive assistance systems.

## 5 Conclusion

Despite the potential of physiologically adaptive cognitive assistance systems to support individuals with MCI, research exploring the use of these systems in the workplace nonetheless remains scarce. This work aims to encourage further research in this area by addressing key barriers to developing real-world implementations, including sensor integration, multimodal data fusion and choice of support strategies, as well as providing design guidelines and a modular framework. In terms of societal impact, it is hoped that this research will help promote the inclusion of individuals with MCI in the labour market.

## Acknowledgments

The author is currently pursuing a cooperative doctorate, supervised jointly by Prof. Dr. Teena Hassan from the *Bonn-Rhein-Sieg University of Applied Sciences* and Prof. Dr. Elisabeth André from the *University of Augsburg*. This work has been funded by the *Ministerium für Kultur und Wissenschaft des Landes Nordrhein-Westfalen* via the *Profilbildung 2022* project *Zentrum Assistive Technologien Rhein-Ruhr* (PB22-076B).

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