Preliminary experimental results on a multidimensional model for cognitive assistance systems in manufacturing

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Preliminary experimental results on a multidimensional model for cognitive assistance systems in manufacturing

BARTOLOMEI Mirco[1,a], BARRAVECCHIA Federico[1,b], REA Maria[1,c], MASTROGIACOMO Luca[1,d], CANNIZZARO Davide[2,e], FRANCESCHINI Fiorenzo[1,f]

[1]Politecnico di Torino, DIGEP (Department of Management and Production Engineering), Torino, Italy

[2]Leonardo S.p.A., Corso Castelfidardo, 22, 10128, Torino, Italy

[a]mirco.bartolomei@polito.it, [b]federico.barravecchia@polito.it, [c]s298826@studenti.polito.it, [d]luca.mastrogiacomo@polito.it, [e]davide.cannizzaro@leonardo.com, [f]fiorenzo.franceshini@polito.it

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Abstract. Cognitive assistance systems aim to enhance cognitive ergonomics by supporting operators in decision-making and task execution, addressing the high demands imposed by modern manufacturing processes. Existing frameworks for characterising cognitive assistance systems are fragmented, lacking a systematic approach to define and evaluate their constituent features. To address this gap, a multidimensional conceptual model is proposed, encompassing five core dimensions: *cognitive functions, autonomy, adaptivity, interaction modality*, and *portability*. A case study is conducted to preliminarily verify the model's applicability by analyzing how variations in these core dimensions influence cognitive load, number of failures, and cycle time. Overall, the study provides two main contributions: (i) a multidimensional conceptual model to bridge the gap in the characterisation of cognitive assistance systems, and (ii) some preliminary findings from a case study in the context of Human-Robot Collaboration (HRC).

Introduction

Modern manufacturing environments impose high cognitive demands on operators due to task complexity, workflow variability, and precision requirements [1]. When cognitive load—the mental effort required to process task-related information—exceeds manageable levels, it can adversely impact performance, productivity, and operator well-being [2]. To address these challenges, cognitive assistance systems, which integrate real-time data, artificial intelligence, and advanced user interfaces, have emerged as a promising solution. By providing relevant process information, guiding task execution, and correcting operator errors, these systems enhance task performance and reduce the likelihood of operator-induced failures [3].

Cognitive assistance can be delivered through a wide range of technologies and modalities, including augmented reality (AR), virtual reality (VR), conversational agents (e.g., voice assistants or chatbots), wearable devices (e.g., smart glasses or wristbands), and context-aware Internet of Things (IoT) systems [4]. Research highlights a variety of applications for cognitive assistance systems. For instance, Leins et al. [5] illustrate how AR improves manual assembly by overlaying step-by-step instructions to enhance accuracy and efficiency, while Funk et al. [6] proposed a system that provides multimodal feedback mechanisms (e.g., visual, auditory, and haptic signals) to prevent errors during assembly tasks. Despite these advances, the field lacks a comprehensive reference model that defines the core dimensions characterizing cognitive assistance. While numerous studies have identified important properties of these systems, their contributions are often limited to specific, non-overlapping aspects, leaving a lack of integration across frameworks

[7]. This gap hinders the development of effective design strategies and limits the systematic evaluation of cognitive assistance systems. The primary research goal is to establish a structured and generalizable framework for the description and assessment of such systems across diverse technologies and application contexts. To achieve this, a conceptual model is proposed, comprising five core dimensions: *cognitive function, autonomy, adaptivity, interaction modality,* and *portability*. Each dimension is associated with a rating scale to enable consistent evaluation. The model's diagnostic capacity was preliminarily evaluated through a controlled experiment designed to test whether variations in the proposed dimensions correspond to measurable differences in cognitive load and task performance.

The paper is structured as follows. The conceptual model section describes the core dimensions of cognitive assistance. The model application section outlines its use in analyzing four configurations of cognitive assistance systems. The experimental section provides preliminary empirical results through a case study on cognitive load and operational performances. Finally, the discussion and conclusions section highlights the model's implications, practical applications, and potential directions for future research.

Conceptual Model of Cognitive Assistance Systems

To develop a comprehensive model, existing conceptual schemes of cognitive assistance [7–11] were examined, and their constituent dimensions were synthesized and integrated into a unified model. The selected models were identified through a focused literature review conducted using a predefined set of keywords in the Scopus and Web of Science databases, with selection criteria emphasizing conceptual robustness and relevance to cognitive assistance; studies were included based on publication quality, thematic alignment, and methodological clarity. The labels assigned to the model's dimensions serve as reference terms, consolidating the implicit meanings of similar concepts across the different schemes, defined as follows:

- *Cognitive functions:* this dimension captures the specific tasks a system performs to support stages of information processing [7,8].
- *Autonomy:* refers to the system's degree of independence in performing assistance actions. This emphasizes the importance of cognitive systems capable of monitoring task execution, perceiving their environment, and making context-aware decisions [9,10].
- *Adaptivity:* refers to the system's ability to dynamically adjust to changes in task demands or operator states, ensuring effective support even under varying conditions [9,10].
- *Interaction modality:* denotes the modes of communication between the system and its user, particularly through sensory channels such as visual, auditory, or tactile interfaces [9].
- *Portability:* defines the extent to which a device providing cognitive assistance can be moved across different environments. The portability of such devices is recognized as a defining characteristic of cognitive assistance systems, enabling flexibility and broader applicability [11].

In the proposed model (see Figure 1), the five core dimensions are hierarchically organized to reflect their roles within cognitive assistance systems. At the foundation is the *cognitive function* core dimension, defining the system's primary purpose by specifying what it does to assist the operator, focusing on information processing stages. The other four dimensions—*autonomy, adaptivity, interaction modality,* and *portability*—are subordinate, describing how the system delivers its support in every information processing stage addressed.

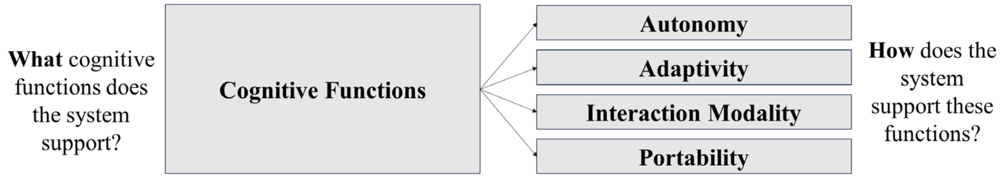

Fig. 1. Conceptual Model of Cognitive Assistance Systems

The Cognitive Functions dimension.

The *cognitive functions* dimension defines what support actions the system provides. Table 1 summarizes the categories of the *cognitive functions* dimension [7,12,13], outlining their descriptions and providing practical examples. For instance, a system that visualizes process parameters and alerts users to deviations performs the functions of *information acquisition* and *information analysis*. In contrast, a system providing step-by-step assembly instructions supports *action selection* and *action implementation*.

By identifying the cognitive functions performed, a critical initial distinction can be drawn between different cognitive assistance systems.

Delivering Cognitive Functions

Analysing a system through the lens of cognitive function enables an initial classification of systems and an assessment of their potential. However, the implementation of cognitive functions can vary significantly, as they can be delivered through different modalities. These approaches can be systematically characterized according to the core dimensions *of autonomy, adaptivity, interaction modality,* and *portability*. To transition from a purely conceptual model to one that facilitates the evaluation and comparison of cognitive assistance systems, the rating scales outlined in Table 2 are proposed. These scales are derived from existing frameworks and adapted to the context of cognitive assistance.

Table 1. Basic categories of Cognitive Functions with descriptions and examples [7,12,13].

Cognitive Functions	Description	Example of Cognitive Assistance
Information Acquisition	Support in perceiving and gathering relevant process data.	A display providing raw process data, e.g. cycle time, machining parameter and process status.
Information Analysis	Assistance in interpreting and processing acquired data to derive meaningful insights	A dashboard displaying trends in system performance for anomaly detection.
Action Selection	Guidance in choosing the most appropriate action based on analyzed information.	A recommendation system suggesting optimal machine settings for energy efficiency.
Action Implementation	Direct aid in executing the selected actions.	Augmented reality overlays showing step-by-step assembly instructions.
Feedback	Support in identifying and correcting errors in task execution.	A visual alert notifying an operator of an error in task execution for immediate correction.

Table 2. Levels and descriptions of autonomy [14], adaptivity [15], interaction modality [16], and portability [11] core dimensions.

Core Dimension	Levels	Description
Autonomy	*L0: Not Performed*	The cognitive assistance system does not perform the cognitive function
	L1: No Autonomy	The system provides information or instructions on demand, but the cognitive function is entirely performed by the human operator.
	L2: Partial Autonomy	The task is performed fully or partially by the system, but either at the operator's request or after receiving the operator's approval.
	L3: High Autonomy	The system independently makes decisions and takes actions, either without informing the user or notifying them only after execution.
Adaptivity	*L0: Not Performed*	The cognitive assistance system does not perform the cognitive function.
	L1: Static	The system provides the same assistance regardless of changing task demands or operator states.
	L2: Reactive	The system adjusts assistance in response to changes in the process or operator state.
	L3: Proactive	The system anticipates changes in the process and the operator state and adapts assistance in advance.
Interaction Modality	*L0: Not Performed*	The cognitive assistance system does not perform the cognitive function
	L1: No Interaction	The system provides assistance without direct user interaction.
	L2: Unimodal	Interaction involves one sensory modality (e.g., visual, auditory, or haptic).
	L3: Multimodal	Interaction engages two or more sensory modalities simultaneously.
Portability	*L0: Not Performed*	The cognitive assistance system does not perform the cognitive function
	L1: Stationary	The device operates in a fixed location and cannot be moved easily.
	L2: Mobile	The device is portable, enabling use in various locations.
	L3: Wearable	The device is attached to the worker during its use.

A Preliminary Experimental Application of the Model

In this section, the proposed model is applied to characterize four representative configurations of cognitive assistance systems used in an assembly process. The experiment aim was to assess the model's ability to distinguish between system setups based on assigned dimension levels, and to examine whether these differences correspond to measurable variations in cognitive load and task performance. Each configuration is defined by two factors: (i) the presence or absence of a UR3e collaborative robot (cobot) (see Figure 2.A), which supports operators in assembly tasks by providing both guidance and physical assistance, and (ii) the type of display used to present assembly instructions, either an assisted reality (aR) device, the RealWear Navigator 520 (see Figure 2.B), or a fixed screen. By combining the two factors, four explicative configurations can be obtained: *Configuration 1* (manual execution with fixed screen), *Configuration 2* (manual execution with aR), *Configuration 3* (collaborative execution with fixed screen), and *Configuration 4* (collaborative execution with aR). The configurations were experimentally evaluated through the assembly of some skateboard variants, with each task involving a different skateboard setup. The components of the assembled skateboard are shown and listed in Figure 3. The four configurations supported the following cognitive functions: *action selection, implementation,* and *feedback*. In *Configuration 1* and *Configuration 2* (manual assembly), cognitive assistance was delivered only via images, videos, and text to guide the assembly process, via either the aR device or the fixed screen, depending on the setup. In *Configuration 3* and *Configuration 4 (*collaborative assembly), the cobot autonomously selected and positioned components based on user input, while still providing assistance on the *feedback* cognitive function via either the aR device or the fixed screen, depending on the setup.

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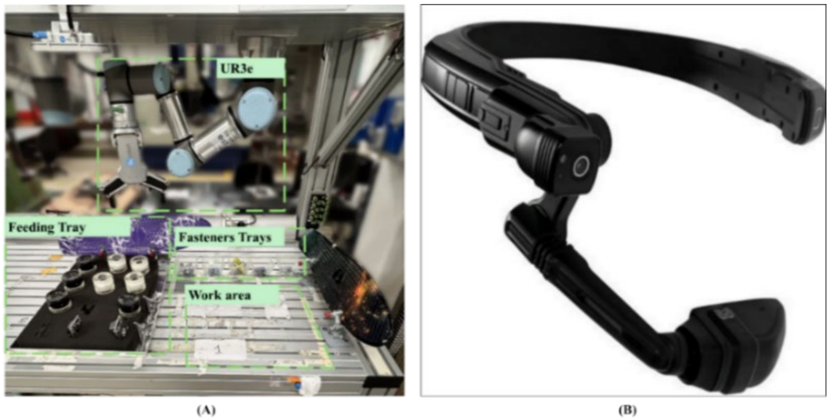
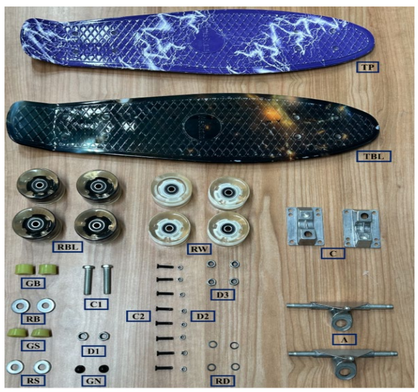


Fig. 2. (A) Overview of the workstation setup; (B) Illustrative picture of the Navigator 520 [17].



Code	Description	Quantity
C	Base plate	2
C1	Kingpin	2
RB	Top cup	2
GB	Bushing	2
RS	Lower cup	2
GS	Cone bushing	2
GN	Pivot bushing	2
A	Hanger	2
D1	Kingpin nut	2
C2	Deck bolt	8
D2	Deck nut	8
RBL	Black wheel	4
RW	White wheel	4
D3	Axle nut	4
TP	Purple skateboard deck	1
TBL	Black skateboard deck	1

Fig. 3. Skateboard components with their corresponding identification codes and descriptions.

The four explicative configurations of cognitive assistance systems were systematically characterised by applying the proposed conceptual model as follows:

- *Configuration 1:* for action selection, action implementation, and feedback, the system provides no autonomy *(L1)* leaving the operator fully responsible for following the instructions and executing the task. Adaptivity is static *(L1)*, offering consistent guidance independent of task or operator status. Interaction is multimodal *(L3)*, as the fixed screen delivers visual instructions and receives input via button presses. Portability is limited since the screen is stationary *(L1)*.
- *Configuration 2:* similarly to *Configuration 1*, for action selection, action implementation, and feedback, system's autonomy is absent *(L1)*, and adaptivity is static *(L1)*, providing uniform support throughout the assembly process. Interaction is multimodal *(L3)*, with the aR system receiving audio input and providing visual information. Portability improves significantly *(L3)* for all the cognitive supported functions performed, as the aR is mounted on the operator's head.
- *Configuration 3:* the robot introduces partial autonomy *(L2)* in action selection and implementation by performing variable tasks independently on operator request. However, despite the visual reference provided by the system, feedback remains fully operator driven *(L1)*. For every supported cognitive function, adaptivity is static (L1), interaction modality remains multimodal *(L3),* and portability is stationary *(L1)*.
- *Configuration 4:* like in *Configuration 3*, robot provides partial autonomy *(L2)* for action selection and implementation. In addition, the aR and the cobot provide multimodal support *(L3)*. Adaptivity remains static *(L1)*, as the system does not adapt to task variations. Portability

is improved *(L3)* for feedback functions, due to the wearable aR device. On the contrary, the robot implementing the action selection and implementation functions is stationary (L1).

Experimental Setup
The experiment evaluated operational performance and cognitive load across the four cognitive assistance system configurations using a within-subject design. Each of the 12 participants, with no prior assembly experience of the selected product (skateboard), completed 4 assembly tasks per configuration. This design minimized the effect of inter-individual variability by allowing each participant to be compared against their own performance across different configurations. In addition, by randomising the sequence of presentation of configurations, the risk of order bias was minimised. Tasks involved identifying, positioning, and fastening components, with varying skateboard base and wheel arrangements in each repetition to prevent reliance on memory. The assembly station setup used for the experiment is shown in Figure 2.A.
Cognitive load was measured using two complementary physiological metrics:

- *Average fixation duration*: ocular activity was recorded via eye tracking device (Tobii Pro-glasses 3). Longer fixations indicates higher cognitive load [18].
- *Skin Conductance Level (SCL):* measured with a wristband wearable device (Empatica E4). Higher SCL are correlated with higher experienced cognitive load [18].

Operational performance was assessed using three metrics:

- *Number of failures*: which combined *product errors* (e.g., incorrect placement or missing components in the final assembly) and *process errors* (e.g., deviations from the prescribed assembly sequence).
- *Cycle time*, the total time taken to complete the assembly process.

Data Processing.
Physiological metrics were standardized using Z-scores to account for inter-individual variability in baseline cognitive load and arousal. The Z-score for each metric was computed using the formula:

$$z_{i,j} = \frac{x_{i,j} - \bar{x}_j}{s_j} \quad (1)$$

where $z_{i,j}$ and $x_{i,j}$ represent the z-score and raw observation for the i-th metric (i.e., average fixation duration and SCL) of participant j, respectively, $\bar{x}_j$ is the mean value for participant j, and s_j is the standard deviation for participant j. Standardizing the data ensured that differences between configurations were not influenced by individual physiological variations. To account for repeated measures nested within participants, a Linear Mixed-effects Model (LMM) was employed. LMM accounts for within-participant variability by modelling repeated measures, controls for between-participant differences as a random effect, and handles task replications across system configurations. The model accounts for the effects of screen type (fixed screen vs aR), execution modality (collaborative or manual), and their interaction, while incorporating a random effect to adjust for individual variability across participants.
Subsequently, ANOVA was conducted to evaluate the statistical significance of the fixed effects. Finally, post-hoc pairwise comparison of Estimated Marginal Means (EMMs) were conducted to enable direct comparisons between the four configurations [19].

Results
Post-hoc pairwise comparisons of average fixation duration, SCL, task failures, and cycle time revealed key differences between the cognitive assistance systems on cognitive load and cycle times.

As shown in Figure 4.A, ocular activity indicated variations in cognitive load across the configurations. Fixation duration, positively correlated with cognitive load, was significantly shorter in *Configuration 4* compared to *Configuration 1* (p=0.008) and *Configuration 2* (p=0.042). This reduction suggests that the combination of robotic autonomy and the portability provided by the aR device in *Configuration 4* distributed the cognitive effort for feedback and guidance more effectively.

Electrodermal activity, measured through *SCL*, provided further evidence of reduced cognitive load in the configuration combining greater autonomy and portability (see Figure 4.B). *SCL* was significantly lower in *Configuration 4* compared to *Configuration 1* (p=0.015), *Configuration 2* (p=0.020) and *Configuration 3* (p<0.001), indicating that the combined effect of robotic support and wearable aR technology helped alleviate cognitive load.

Considering the performance metrics, cycle time exhibited a trend opposite to that of cognitive load. As shown in Figure 4.C, *Configuration 1*—characterized by manual operations and a fixed screen—had significantly shorter cycle times compared to *Configuration 2* (p=0.01691), *Configuration 3* (p=0.0138), and *Configuration 4* (p=0.006). These results indicate that, in this particular scenario, the configuration without the robot and aR was the most efficient. No statistically significant differences were observed in terms of failures rates.

These preliminary results indicate that cognitive assistance systems with higher portability and autonomy, such as *Configuration 4*, reduce cognitive demands. However, these benefits come at the cost of efficiency, as reflected by longer cycle times.

Discussions and conclusions

This work presents a multidimensional conceptual model for characterizing cognitive assistance systems and some preliminary results of its application.

The model integrates key attributes of cognitive assistance into a comprehensive framework, defining five core dimensions: *cognitive function, autonomy, adaptivity, interaction modality,* and *portability*. The hierarchical organization of these dimensions highlights their interplay, with *cognitive function* defining the system's purpose and the other subordinate core dimensions specifying the mechanisms of their implementation.

The experimental results show that the model proves effective in distinguishing cognitive assistance systems based on their characteristics and their impact on cognitive load and task performance. The preliminary results suggested that, in the specific scenario examined, wearable-assisted reality systems and robotic assistance may be effective in reducing cognitive load, highlighting the model's potential to address the design of cognitive assistance systems.

Despite its strengths, the proposed model has some limitations. It assumes an independent structure among core dimensions. As a consequence, potential interdependencies remain underexplored, warranting further investigation. Finally, while evaluation scales are suggested for each core dimension, their practical implementation and standardization across different systems are yet to be validated. These limitations appear as valuable opportunities for future research to enhance the proposed model. Efforts should focus on refining the model, verifying its applicability across diverse contexts, and possibly broadening the range of rating metrics to achieve a more comprehensive understanding of cognitive assistance systems. Finally, the model could be useful as a reference framework for developing a taxonomy of cognitive assistance systems and creating practical tools to support their design.

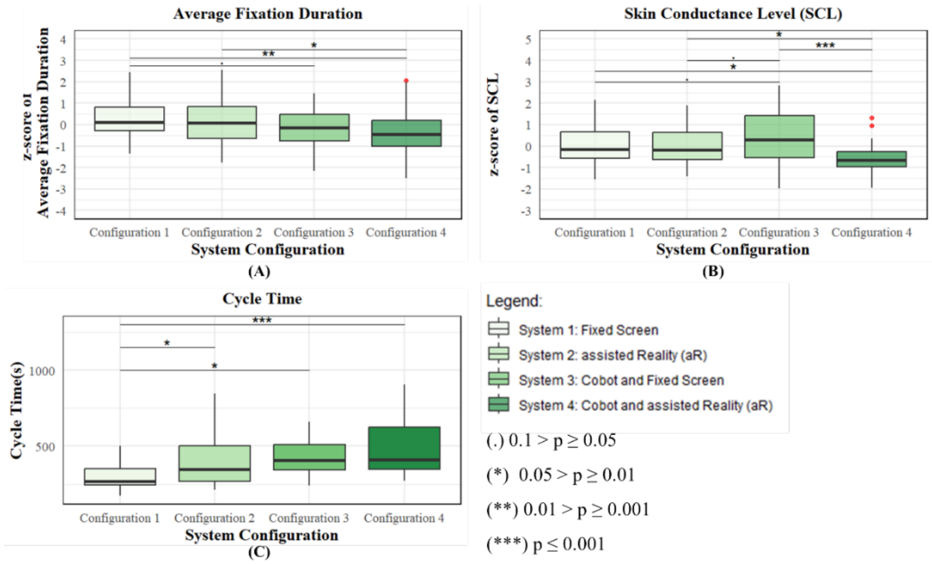


Fig. 4. Cognitive load and cycle time across four system configurations. (A) Boxplots of the distributions of z-scores of Average Fixation Duration. (B) Boxplots of the distributions of z-scores of SCL. (C) Boxplots of the distributions of Cycle Times.

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