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Breaking Barriers: Digital Personal Assistants for the Inclusion of Workers with Disabilities in Production

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Abstract

INTRODUCTION: This paper introduces Digital Personal Assistants (DPAs) as tools to support inclusive employment for workers with disabilities in industrial production.
OBJECTIVES: The aim is to design a DPA that enables barrier-free access to work-related information.
METHODS: DPAs are developed for multiple devices, focusing on accessibility, and task support—co-designed with workers with disabilities.
RESULTS: A possible implementation of a DPAs is shown in this paper.
CONCLUSION: User-centered DPAs can help reduce barriers and support inclusion in production.

Keywords: Disabilities in Production, Digital Personal Assistance, Cognitive Production

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1. Introduction

As the global population continues to grow, many industrialized nations are simultaneously experiencing demographic decline [1]. To maintain living standards and ensure the reliable supply of everyday goods, it is essential to implement strategies that enhance production capacity. While automation presents part of the solution, it alone will not suffice [2]. Unlocking the full potential of human labor remains critical—especially by integrating often-overlooked workforce segments. One such untapped resource lies in workers with disabilities, who comprise a significant portion of the global population yet remain underrepresented in industrial production [3]. Despite decades of policy attention, the employment gap e.g. for workers with disabilities aged 20 to 64 in the European Union has seen only marginal improvement, pointing to enduring structural barriers in labor market inclusion [4]. Recent studies emphasize the need for inclusive workplace design, targeted vocational training, and supported employment models to close this gap and realize the full societal and economic potential of this resource [5].

2. State of the Art

In the domain of industrial production, several studies have investigated the integration of workers with disabilities and its impact on organizational performance. Recent findings suggest that workforce diversity—including the inclusion of workers with disabilities—can enhance productivity, particularly when teams include a moderate representation across different disability categories. Nevertheless, despite these encouraging developments, the potential of workers

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with disabilities remains significantly underutilized, especially in production-intensive sectors [6–10].

Digital technologies have shown promise in reducing barriers and facilitating the integration of workers with disabilities into industrial production environments: Physical barriers—such as inaccessible infrastructure—are often readily identified and addressed through tangible measures like step-free access or height-adjustable workstations [11]. The associated costs and benefits of such physical adaptations are quantifiable and can be evaluated in monetary terms. In contrast, cognitive barriers—such as learning difficulties—often remain unaddressed [12]. These barriers are less visible and are frequently overlooked due to a lack of awareness or the absence of appropriate tools and methodologies to mitigate them, especially in production environments.

To support industrial organizations in assessing the feasibility of integrating workers with disabilities, [13] proposed a methodology based on impact factors, enabling low-effort evaluations of Industry 4.0 technologies in relation to the type of disability and the associated cost-benefit considerations. Another approach, developed by [14], utilizes a methodology, which presents a structured overview of adaptive technologies that can be feasibly implemented in assembly tasks in production also related to workers with disabilities. Overall, the progressive development of digital technologies holds significant potential for lowering access barriers in production. This ongoing entanglement of digitalization along with human-centered approaches are often referred to as "cognification," highlighting the increasing integration of intelligent systems aimed at supporting diverse cognitive needs in the workplace.

Cognitive industrial systems refer to machines and processes endowed with cognitive capabilities that enable them to perceive, interpret, learn, reason, and make context-aware decisions—surpassing the limitations of traditional rule-based control systems. These systems evolve through a multi-stage process: (i) semantically perceiving sensor data, (ii) identifying causal relationships to achieve contextual awareness, (iii) reasoning to support informed decision-making, and (iv) autonomously learning and adapting to dynamic environments. Over the past decade, substantial progress in this field has been made by numerous research groups [15–18].

Recently, cognitive approaches have been successfully applied across various domains, including cloud and edge computing [18], industrial production [19–22], digital twin architectures [23], human-centered systems [24–26], intrusion detection [27], and predictive maintenance [28]. These systems represent a paradigm shift in production technologies by delivering autonomy, adaptability, and interaction capabilities that closely resemble those of human operators. They are particularly advantageous in scenarios involving small-batch or highly customized production, where the ability to manage uncertainty, respond to unforeseen events, and adapt rapidly is critical—while simultaneously maintaining the precision and reliability characteristic of automation [15].

Studies indicated that cognitive technologies can significantly reduce risks and error rates on the assembly line, thereby enhancing process reliability [29]. The overarching objective is to increase operational flexibility while expanding the capabilities of both workers and machines [30]. Communication and safety systems are essential for ensuring the smooth operation of production machines at the shop floor level, as they serve as the foundation for effective human-machine collaboration [31]. Moreover, qualitative improvements in assembly processes through cognitive technologies have been documented, highlighting their transformative potential [32].

The successful implementation of such advanced technologies like cognitive technologies requires consideration of broader contextual factors. As shown in [33], a conceptual framework for designing assistive technologies in the user's working environment was developed to guide the integration of digital tools, with particular attention to their benefits and constraints. A central prerequisite for all cognitive technologies is the availability of high-quality data. This includes not only technical process data but also human-centered data that provide insight into workers' physical and cognitive states. The effectiveness of cognitive production systems relies heavily on the quality, relevance, and timeliness of these data streams.

However, as emphasized in [34], the quality of human-related data often depends on voluntary input from workers, particularly in cases where expertise, experience, and tacit knowledge are required. Factors such as years of experience, skill level, and defect rates play a critical role in evaluating and validating these data. Trustworthy data acquisition is a key challenge in this context.

Mitigating this disparity, emerging research illustrates the potential of digitalization as an enabler of worker state detection, particularly regarding stress and workload in future production systems [35]. For example, [36] demonstrated the accurate prediction of physiological workload during of workers executing various assembly tasks using machine learning approaches.

Equally important is the delivery of relevant and actionable information to workers. As shown in [37], well-designed, user-friendly dashboards can significantly enhance transparency and provide value by making process data easily accessible.

In the context of accessible design—particularly for workers with disabilities—barrier-free information interfaces are essential. According to the Global Accessibility Reporting Initiative (GARI), currently over 150 accessible digital features have been defined especially for smartphones, of which 118 are already implemented in devices widely used across Europe [38]. These include features for users with vision impairments, e.g. screen readers, text-to-speech, voice assistants and for users with hearing impairments, e.g. haptic feedback, visual alerts, vibrating notifications, and closed captioning.

These accessible digital features are considered as industry standards and play a crucial role in promoting inclusion across markets [39]. Although such technologies are widely accepted and frequently used by workers with disabilities in everyday digital contexts at their smartphones, their adoption in industrial production environments remains limited. This highlights a significant opportunity for more inclusive digital system design in production, because this untapped workforce segment is often overlooked in digitalization and cognification of industrial processes.

3. Research Question

This raises the central question of how digital systems in production environments must be designed to provide meaningful support for the sustainable integration of workers with disabilities. Furthermore, it prompts an examination of which accessibility features—many of which are already widely implemented in smartphones—can offer significant added value when adapted to industrial and production environments.

4. Methodology & Approach

To address the research question outlined above, the study is structured into two main phases. In the first phase, a Digital Personal Assistant (DPA) is developed; in the second phase, its use will be evaluated through pre- and post-implementation questionnaires. This paper presents the results of the first phase: the development of the DPA.

4.1 Digital Personal Assistant

A DPA is a compact, portable computer system designed to assist workers in performing various tasks. Support may take the form of context-sensitive information during task activities, ranging from simple visual cues within the interface to more comprehensive step-by-step operational instructions. DPAs can be implemented on a variety of portable computing devices for several applications: (i) smart glasses for warehouse picking and order fulfilment, (ii) tablet PCs for accessing instructional videos during training, (iii) stationary PCs for displaying assembly instructions, (iv) smartwatches for real-time hazard alerts, (v) smartphones for safety notifications, (vi) machine-integrated systems for providing quality-related guidance. More broadly, DPAs can be categorized into three principal types of use cases:

- Support systems
- Adaptive assistance systems
- Tutoring assistance systems

Support systems facilitate access to existing analogue knowledge in digital form or provide task-specific guidance via simple user interfaces. Common applications include digital manuals, instructional videos, assembly and maintenance guides, quality and safety notices, process documentation, skills and qualification management tools, and classical knowledge management systems.

In contrast, adaptive assistance systems leverage sensor-based data to capture work processes, user context, and environmental conditions, allowing for personalized adaptation to individual workers and tasks. Examples of such systems include interactive work instructions, pick-by-light technologies, context-sensitive information delivery, and user interfaces that adapt in terms of language or control elements.

Finally, tutoring assistance systems represent a specialized subclass of adaptive systems, aimed at supporting learning within the flow of work. These systems enable learning-friendly environments and deliver situational, task-relevant knowledge as needed. Typical implementations include training and educational platforms, portable knowledge and learning systems, and augmented reality–based tools for technical service and maintenance support.

Based on this, a DPA were developed, implemented within a use-case providing company, and equipped with context-specific production content.

4.2 Technical Implementation

The DPA was implemented using Microsoft Power Apps, a low-code platform used to create user-friendly and adaptable interfaces. Acting as the front-end, Power Apps connects to existing internal systems as the data source, enabling secure and dynamic communication between employees and company data. Its availability within many companies' Microsoft ecosystems eliminated additional costs, and its compatibility with various devices ensures accessibility across workplaces. The platform's flexibility also allows seamless integration into existing workflows.

4.3 Focus on Accessibility

A central focus of the development of the DPA was on accessibility, adhering to the principles of inclusive design as recommended by the Global Accessibility Reporting Initiative (GARI). A critical factor for successful deployment was the creation of an accessible user interface tailored to the needs of diverse user groups, particularly those with disabilities.

The user interface was designed to support workers with various disabilities. For visual impairments, features include magnification, zoom, high contrast, large fonts, and a read-aloud assistant for all content, including hidden text. Haptic feedback enhances touchscreen interaction. Hearing impairments are addressed through visual alerts and, in future, sign language videos. The interface also supports stylus input for limited dexterity and provides subtitles and visual alternatives for speech and language disabilities. Cognitive accessibility is prioritized through a simple, intuitive interface featuring clear visuals, memory aids, and consistent colors. Content is presented in short, plainlanguage sentences, and the absence of screen timeouts helps reduce workers' stress.

5. Results

Based on these findings, the DPA was developed. The DPA is structured as described below and may serve as a reference model for diverse applications in production environments. The use case presented focuses on the control electronics of a small electric motor. Although this control electronic is produced in high volumes, it is characterized by a high degree of product variability, with over 10 million possible variants. This complexity makes the production process particularly prone to errors, which is why the added value of the DPA is demonstrated using this specific product, illustrating the system's practical implementation in a real-world production context.

Upon launching the DPA, workers are required to authenticate themselves to gain access to the system, as depicted in Figure 1. This authentication can be performed manually by entering the employee identification number or, alternatively, through the use of an employee ID card, enabling rapid and contactless authentication.

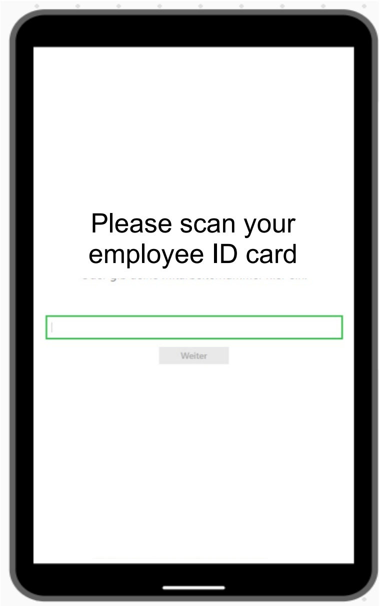

Figure 1. Start Screen and Authentication Process

After successful authentication, workers are presented with a personalized task overview, illustrated in Figure 2. Within this interface, they can select specific tasks that are relevant to their assigned workstation or role. This targeted selection supports efficient task execution and minimizes the potential for errors. Additionally, a lexicon module granting workers access to comprehensive information related to their assigned tasks. This lexicon includes a glossary of individual parts, tools, and methods relevant to the production. In addition, company-specific information—such as the organizational chart, supervisors, and other structural details—is also accessible through this lexicon.

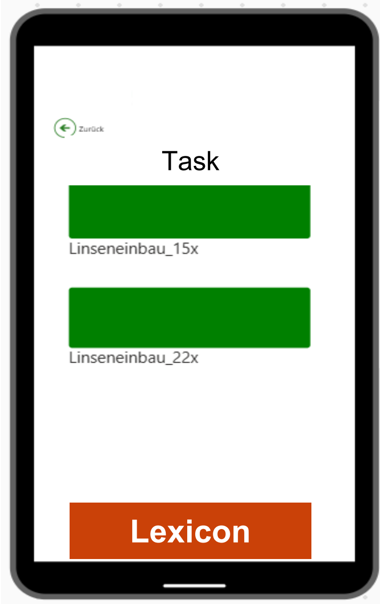

Figure 2. Task Overview and Information Access

The system automatically highlights safety and work instructions that have either been recently updated or not accessed by the workers for an extended period, shown in Figure 3. These documents are clearly listed within the DPA, ensuring that critical information is brought to the workers' attention. Workers are prompted to review these documents thoroughly and are required to digitally confirm their understanding by providing an electronic signature. These signed confirmations are systematically recorded and can be used as official documentation for training verification and certification purposes. This process ensures compliance with occupational safety standards and supports continuous knowledge maintenance in the production environment.

After completing the authentication process and signing the relevant safety instructions, the worker is directed to the main interface. Within the main interface of the DPA, depicted in Figure 4, workers have access to essential resources relevant to their current tasks. At any point during executing their tasks, they can choose between 4 categories of information, including

- Working Environment Module
- Operational Instruction Module
- Safety Guideline Module
- Video Description Module

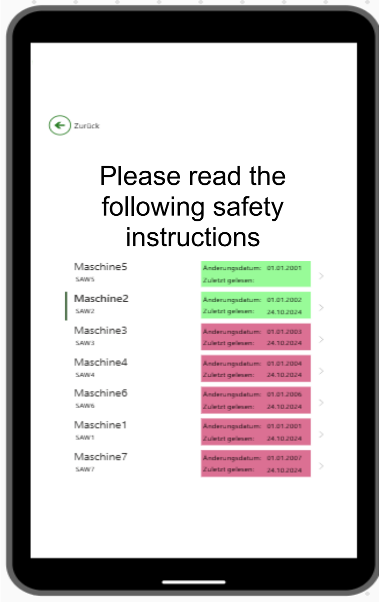

Figure 3. Review of Safety and Work Instructions

Figure 4. Main Interface

This modular structure of the DPA ensures that workers receive the specific type of support they need in real time, promoting task efficiency, adherence to safety protocols, and ease of understanding through multiple formats of instruction.

The working environment module provides workers with detailed information about the parts to be used in their current tasks, illustrated in Figure 5. It ensures clarity regarding required materials and supports process accuracy and quality measures. In addition, the system offers real-time feedback on faulty parts, enabling immediate corrective action.

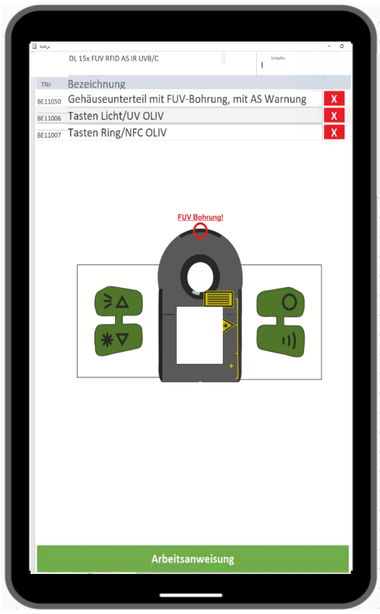

Figure 5. Working Environment Module

The operational instruction module displays interactive work descriptions tailored to the worker's assigned tasks as shown in Figure 6. To enhance comprehension, instructional videos are integrated into the DPA, visually illustrating key tasks and procedures.

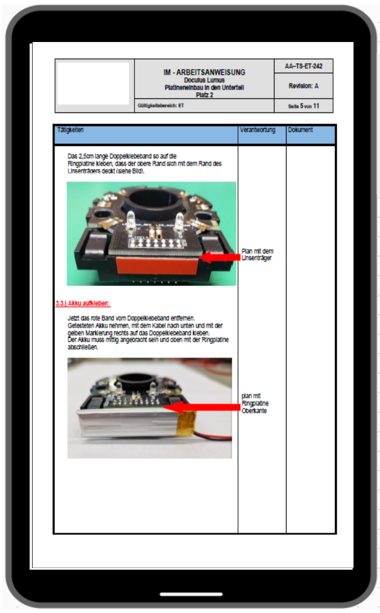

Figure 6. Operational Instruction Module

Workers can access this content at any time and are encouraged to review it at their own pace, ensuring individual understanding and supporting autonomous, informed task execution. This approach fosters procedural reliability.

The Safety Guideline Module is structured in a similar manner. It provides access to overarching safety instructions that extend beyond the workstation-specific guidelines already addressed during the authentication process. This module covers tool usage, specific work procedures, as well as information on materials, operating supplies, and auxiliary substances. Additionally, it includes a first aid checklist and allows for the reporting and documentation of near-miss incidents related to the tools and materials used.

The video description module has been created for each individual task according to Figure 7. These videos have been edited and optimized to visually demonstrate the tasks in a clear and accessible manner, supporting intuitive learning and reducing the risk of misinterpretation. As a future enhancement, the integration of sign language into these videos is planned, further improving accessibility for workers with hearing impairments.

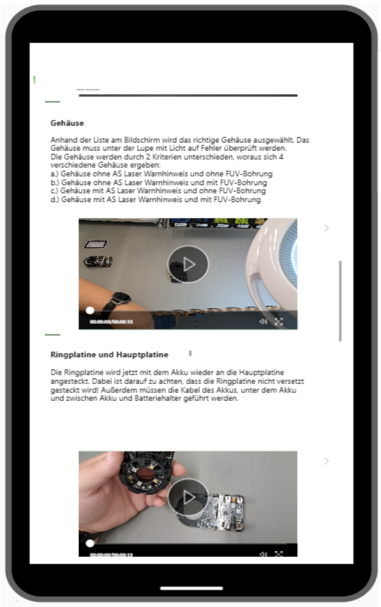

Figure 7. Video Description Module

6. Conclusions & Outlook

In conclusion, this paper examined the necessity of Digital Personal Assistants as inclusive technologies, particularly for workers with disabilities in industrial production environments. It outlined the design and functionality of such a DPA, providing a detailed description of its implementation and potential applications.

An important aspect for the future research is the second project phase mentioned in the section 4, which will focus on the evaluation of the DPA based on pre- and post-implementation questionnaires. To carry out the evaluation, so-called usability questionnaires from software development will also be used.

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