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Towards Sustainable and Technology-Enabled Engineering Psychology in Production

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Abstract. This paper explores the development of digital systems to identify and reduce cognitive stresses in contemporary manufacturing environments with increasing numbers of robots and smart machines. To achieve this, the study attempts to answer the following research question: How can technology-driven advancements in engineering psychology be leveraged to foster more productive, ethical, and psychologically supportive collaboration between humans and robots in the context of modern manufacturing environments? The study explores relevant literature to gain deeper insights into the subject succeeded by the development of a prototype composed of two digital solutions. By improving cognitive ergonomics through the detection and recognition of non-verbal cues, as well as reducing cognitive stress by providing real-time information on the positions of mobile robots, this study offers potential solutions to the social and psychological challenges of human-robot collaboration. The paper concludes with an analysis of the final prototype, a discussion on sustainability implications, and recommendations for future research. Overall, this research aims to bridge the gap between human workers and technology in the manufacturing sector, facilitating a harmonious and productive collaboration that aligns with the goals of Industry 5.0.

Keywords. Industry 5.0, Engineering Psychology, Human-Robot Collaboration

1. Introduction

The advent of Industry 5.0 (I5.0) signifies a shift towards a human-centric approach in the industrial landscape, where human workers engage in collaborative endeavors with robots and intelligent machines to execute high-value tasks [1]. However, this transition raises substantial concerns regarding the ethical integration of such collaborative systems, necessitating a careful exploration of ethical principles [2]. The challenge lies in establishing seamless interconnections among workers, organizations, and evolving technologies, with emphasis on the critical role of a smooth transition in this evolving ecosystem [3]. Notably, the workplace landscape is witnessing a pronounced shift from

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physical to psychological risks, marked by mental overload and increased work density resulting from the dynamic and flexible nature of smart manufacturing activities [4]. Recognizing these challenges, digitalization emerges as a pivotal tool, not only in comprehending these concerns but also in driving effective solutions.

1.1. Problem Description

In contemporary manufacturing environments characterized by a growing presence of robots and smart machines, the human workforce faces escalating cognitive stresses. These challenges are exacerbated by the need for harmonious collaboration between humans and technology, a cornerstone of I5.0. The overarching problem centers on the development of digital solutions to enhance HRC within these evolving industrial landscapes. The aim of this paper is to develop such solutions with focus on addressing the cognitive ergonomics of Human-Robot Interaction (HRI), including the recognition of non-verbal cues, while also mitigating cognitive stress through the provision of real-time information on mobile robot positions.

1.2. Research Question

The core challenge can be articulated as follows: How can technology-driven advancements in engineering psychology be leveraged to foster more productive, ethical, and psychologically supportive collaboration between humans and robots in the context of modern manufacturing environments? This question calls for innovative approaches that blend engineering psychology, technology, and sustainability to facilitate a seamless transition into I5.0.

The rest of the chapters is structured as follows: an unstructured search of related work, detailed descriptions of the research approach, prototype development and results, and a discussion section involving sustainability implications and future directions.

2. Related work

Human Factors Engineering, with a focus on human-systems integration, human-computer interaction, and user-interface design, plays a pivotal role in comprehending human interactions with technology [5]. Engineering psychology, a subdiscipline of psychology, further refines this understanding by emphasizing cognitive aspects over physiological concerns, especially in design and evaluation [5]. During the design of a system involving both humans and technology, human cognitive capabilities and processes should be taken into consideration to obtain the necessary knowledge for reconciling technical possibilities with human needs [6].

Transitioning into HRI, recent studies have explored HRI standards with a spotlight on control systems and collaboration methodologies in manufacturing, anticipating increased adoption by Small and Medium-sized Enterprises (SMEs) [7]. However, a significant gap between theoretical research and practical implementation in real industrial settings hampers the seamless integration of laboratory-based cobotic technology into smart factories [8]. The discourse on HRI recommends a Human-Centered Design (HCD) approach, emphasizing the importance of placing humans at the core of manufacturing systems for fluid, safe, and satisfactory interactions [9].

Key enabling technologies of Industry 4.0 (I4.0) provide new opportunities for physical, cognitive, and sensorial assistance, empowering workers for enhanced productivity without replacing them [10]. Assessing the pros and cons of I4.0 from environmental and social aspects is imperative before technical implementation to prevent negative psycho-social effects on the workforce and the manufacturing society at large [11]. Artificial Intelligence (AI) utilization in conjunction with Human-Computer Interaction (HCI) has shown promise in breaking down and understanding physical and mental aspects, creating foresight models for risk prevention, especially in the context of psychological disorders [12]. The synergy of AI, HCI, and psychology has influenced and continues to drive solutions for mental health [13].

More particularly in manufacturing environments, the integration of robots and smart machines has introduced occupational stresses, affecting workers' mental health and overall productivity [14]. Addressing these challenges requires reciprocal interaction between humans and robots, where robots respond to human behaviour, creating a robust communication channel [14]. Implementing customized robot actions based on employees' psychological states could lead to a psychologically safer workplace and improved HRC [15]. A promising approach to reduce mental stress involves providing workers with notifications before executing high-risk activities [14]. Research discussed in [16] evaluates the impact of advanced notice of robot motions on human mental stress. Comparative experiments demonstrate that providing advance notice of the maximum speed of robot motion can effectively reduce workers' mental stress.

Ensuring the well-being, safety, and health of workers is crucial for a sustainable industrial ecosystem, necessitating a human-centered production approach [17]. Concepts like "Social Smart Factory" and "Human Cyber-Physical Systems" advocate for considering human elements in the production system for smarter decision-making in manufacturing environments [18]. The term “Operator 4.0” emphasizes the need for workers to adapt to and excel in an environment where intelligent technologies play a significant role, requiring a blend of traditional skills and proficiency in interacting with and managing advanced technological systems [19]. Future directions indicate exploration of intelligent human-machine interfaces, interaction technologies, and adaptive control systems to further develop human-automation symbiosis in the Factory of the Future [20].

In summary, the literature underscores the significance of Human Factors Engineering and its evolution into the realm of HRI in manufacturing settings. While advances in I4.0 and AI-driven technologies present promising opportunities, the existing gap between theoretical research and practical implementation in real industrial contexts poses a critical challenge. The need for a HCD approach and the integration of customized robot actions based on employees' psychological states are key findings. However, the limited exploration of such implementations emphasizes the existing gap and calls for further research to bridge theoretical concepts with practical applications, specifically in the context of HRC and its impact on worker well-being and productivity. Addressing these gaps is crucial for the successful transition to I5.0, aligning with the overarching goal of creating seamless and psychologically supportive collaboration between humans and robots in modern manufacturing environments.

3. Research Methodology

3.1. Research Approach

The research design of this study aims to bridge the gap between theoretical research and practical implementation of the subject matter. The maturity level in the research area of HCD and HRC applied in manufacturing processes is at a medium state, and the area itself is relatively new. Papers on the subject have been emerging over the past 30 years, with a rapid increase in the past decade.

To validate the existing theoretical background and link it to a real-case industrial context, the authors employed an experimental approach, specifically using the Systematic Parameter Variation method, as defined by [22]: "Systematic parameter variation represents a type of quasi-experiment where several variables known to be essential are kept constant, while other variables are manipulated and carefully measured until an optimal solution is found." This study follows this approach, maintaining essential constant variables such as the state of the system - necessitating human-robot collaboration to achieve tasks and productivity goals - while manipulating variables related to the integration of technology that may affect the psychological state of the worker. The study adopts an abductive pattern, aiming to explain experimental results by providing reasonable explanations and making educated guesses to further develop knowledge in the field.

3.2. Experimental Design

Both experiments were set up to simulate a production logistics facility. The setting was formulated as workstations with human employees in distance with each other and Automatic Mobile Robots (AMRs) transferring materials between the stations. The stations include one main workstation where the human employee is stationed, and three passing stations where the AMR might stop during a route. These were the setup parameters, which were kept constant throughout the experiments.

3.2.1. Experiment 1: Cognitive Stress Reduction

The first experiment aimed at reducing cognitive stress of workers by providing information on the movement of the collaborating automatic vehicle. According to [21], providing workers with notifications before important events – for example, an AMR arriving at the station to pick up an order that is not yet complete – reduces mental stress. For this purpose, a network of proximity sensors was designed to be implemented in the simulated production logistics facility to collect information on the AMR's position and provide appropriate visualization of this information to the worker at the station.

The constant parameters of the experiment, besides the aforementioned, also include the positions of the stations and, consequently, the distances between them. The parameters possible to control were the types of sensors constituting the network, the positioning of the sensors, the number of stations utilized for the experiment and the type of notification/visualization shown to the worker. The output variable would be the confirmation that the worker was accurately notified of the estimated time of arrival (ETA) of the AMR to the workstation. Further experiments are required and recommended by the authors to evaluate the levels of stress of the employee to verify reduction through this installation.

3.2.2. Experiment 2: Emotion Monitoring

The second experiment focused on monitoring the emotional state of the employee using computer vision for facial emotion recognition. The aim was to establish closed-loop cognitive communication between the AMR and the human worker by recognizing non-verbal cues, interpreting the emotions behind the cues, and acting accordingly.

Constant parameters include the preexisting AMR at the laboratory facilities, with its respective mapping and routing system, the use of a pretrained algorithm due to time restrictions and the physical characteristics of the testing subjects. The combination of the latter two leads to biased results, stemming from the subjectiveness of the human emotions determined by personal and cultural differences [22] [23]. Consequently, the results might not be optimal and unbiased to the subject in front of the camera. The issue will be addressed later in the discussion chapter. For the experiment, it was considered as a parameter out of the authors' control.

The parameters that were possible to control in this case were the choice of a pretrained Machine Learning (ML) algorithm, the actions of the AMR and the range of human emotions classified in certain categories. The output of the experiment was expected to be the AMR performing an action based on the emotion that it has identified on the human employee. Also in this case, further evaluations are required and recommended to assess the contribution of this digital solution to the workers' well-being, or even further to evaluate the psychological effects within a cyber-physical system (CPS).

4. Prototype Development

The authors have confidence in the idea that the world manufacturing ecosystem is shifting towards I5.0 and global trends are pushing for more human-oriented conditions on the shop floor for maximized resource utilization and socially sustainable production. In search of an idea leaning towards these shifts, market research was conducted and revealed a gap in assessing and acting on the psychological state of employees, as well as incorporation of this information into production flows.

Ideas were generated through brainstorming, the focus of which was on developing end-to-end solutions, considering the stress levels of workstation employees. The main requirement for the solutions was to be aligned with the objective, as well as the available equipment in the laboratory where the experiments would be conducted. For this research, the experimental scenario took place in a laboratory at KTH Royal Institute of Technology in Södertälje, Sweden. The laboratory simulates material handling facilities with several workstations. The equipment included Arduino microcontroller kits with various sensors, a webcam, and a MiR250 AMR.

4.1. Cognitive Stress Reduction

For the first experiment, an AMR transfers materials and components between these workstations. The main assumption made for the first experiment is that the stations are far apart from each other, resulting in limited communication between the workers and sole collaboration with the AMR. The authors assume that the sensors operate within the design and manufacturing parameters of the available ones in the laboratory, for example, a maximum range of 400cm for the ultrasonic sensors.

Among the available sensor options, ultrasonic sensors were chosen for this experiment. They were selected over laser sensors and other proximity sensors due to their wider angle of detection and suitability for the required application. It should be noted that the AMR already had position trackers installed, rendering other sensor technologies redundant. However, the experiment aimed to make a case for leveraging non-smart technologies for sustainable production logistics.

An Arduino circuit board was connected with the ultrasonic sensor and programmed to provide real-time distance of the moving AMR performing pre-assigned missions. The authors decided to use one ultrasonic sensor at the workstation instead of a network connecting the various stations, due to negligible distances between them in the laboratory environment. However, the system can be augmented with many sensors along the AMR path for more accurate information for the operator of the robot's approximate ETA.

The output of the Arduino code was integrated into Node-Red, a visual programming tool, where a function was utilized to convert the real-time distance to ETA. To present the collected data in a user-friendly manner, Node-Red's User Interface was utilized for visualization, as shown in Figure 1. This visual feedback system served as a warning mechanism to reduce work hazard risks for the station operator.

On the practical aspect of the experiment, the setup was sensitive to the appropriate edge design; for example, choosing of wireless or wired sensors, appropriate sensor sensitivity, sensor range, edge devices interoperability, and sensor positioning.

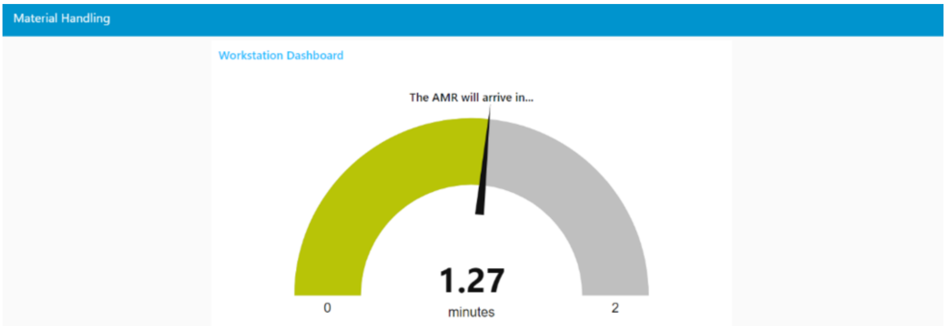

Figure 1: ETA Dashboard

4.2. Emotion Monitoring

In the second experiment, the initial design was to install a camera on the AMR to capture non-verbal cues from human employees and utilize an algorithm to understand their emotional states. This proved to be a challenge because of image depth, scale-space factors, face angle (affine), and motion and optical flow variance [24], hence placing the camera at the workstation proved practical. During a review of the design, it was decided to utilize a laptop webcam installed in the workstation, for stable resolution. The webcam provided adequate resolution and compatibility with the rest of the system, ensuring reliable and accurate data capture for emotion recognition purposes.

A ML algorithm was utilized to interpret facial expressions and trained with secondary data, open-source and available on the internet. The testing of the algorithm occurred through participatory observation. The pre-trained ML library which was used for this experiment is called DeepFace, an open-source project written in Python and licensed under MIT License. The decision was based on the findings of [25], where it is investigated how the facial signals expressed by the human operator can be collected and analyzed via deep learning algorithms. The results are shown in Table 1 in descending order by training accuracy score.

The emotional classes of the ML model were the following: happy, frustrated, and neutral faces. The extra features attributed through the model were gender (female, male) and race (white, black, Asian). The main assumption for this experiment was that the ML algorithm is unbiased regarding these categories.

Table 1. Machine learning algorithms for Facial Emotion Classification with respective training accuracy [25]

Name	Training Accuracy	Name	Training Accuracy
ArcFace	99,83%	VGG19	96%
SphereFace	99,42%	FaceNet	95,12%
CosFace	99,33%	Alex-Net	94,4%
VGGFace	98,95%	ResNet50	79,11%
DeepFace	97%	Inception v3	78,1%
DenseNet201	97%		

As for the correspondence of the AMR to the employee's emotional state, three responses were deployed. In the first case when a happy face was detected, the AMR was approaching the station and, with the use of natural language, it responded "Oh! You look happy today! What's on the menu?", creating a discourse. In the case of a neutral face, the AMR just completed its mission and moved on. In the final scenario where the employee was frustrated, angry, or sad, the AMR kept a safe distance and responded in natural language syntax like "I hate to see you like this. What's wrong? Do you want me to give you some space?".

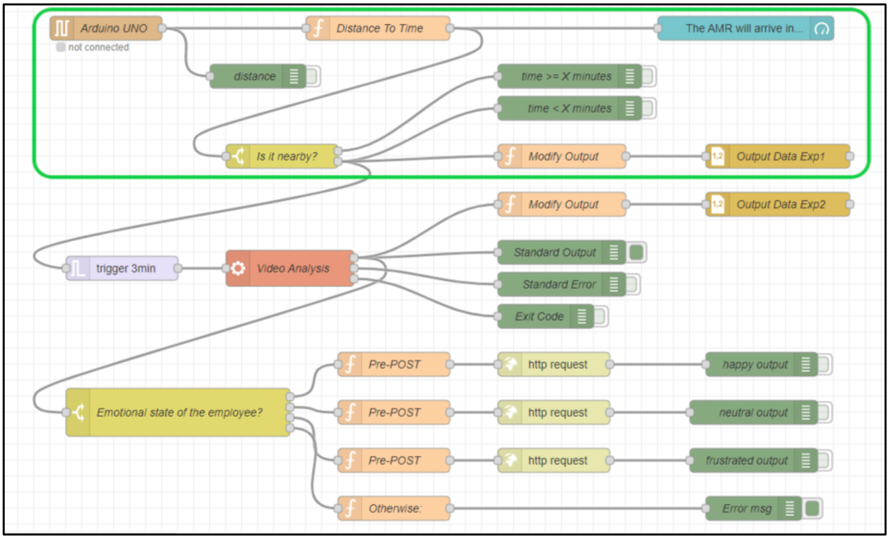

Figure 2. 1st Experiment in Node-Red

Although it is not in the delimitations of this project, the authors aimed to make the system intelligent and connected by using output data from the first experiment as trigger information for the second experiment. More specifically, when the AMR is sufficiently close to the station, visual to the worker through the human-machine interface, a background connection triggers the webcam used for the computer vision to analyze emotional state of the worker, thus integrating the two solutions. The integrated system is visible in Figure 2 and 3, with the two experimental parts highlighted respectively.

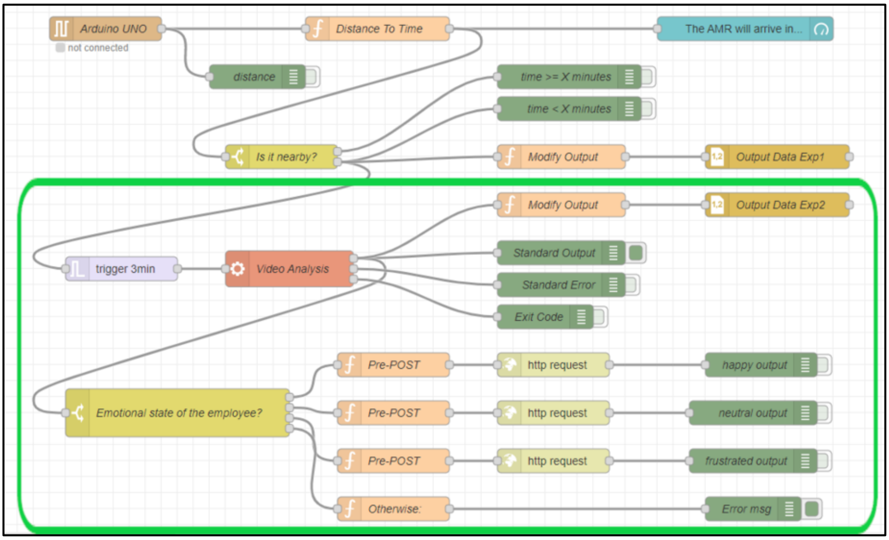

Figure 3. 2nd Experiment in Node-Red

5. Results

For the first experiment, ultrasonic sensors were strategically chosen for their wider angle of detection, aligning with the experiment's non-smart technology focus for sustainable production logistics. The ultrasonic sensors, integrated into Node-Red, provided real-time data on the AMR's position and ETA at the workstation. This visual feedback system effectively warned the station operator of the approaching AMR, contributing to reduced work hazard risks.

The results of the emotion monitoring experiment demonstrated the feasibility of integrating ML algorithms into human-robot interaction scenarios. The responses, tailored to the detected emotional states, showcased the potential for creating a more empathetic and responsive human-robot collaboration environment. The computational costs resulted in system latency with regards to image analysis. The open-source image analysis algorithm displayed some errors and bias. The AMR path seems to be a critical constraint for with many obstructions will make the AMR stop.

Node-Red enabled seamless integration between the ML model, AMR control, and data storage, serving as a centralized platform for managing workflow and ensuring smooth operation. The integrated system demonstrates potential for creating a holistic approach to human-robot collaboration, addressing both physical and emotional aspects.

6. Discussion & Future research

Addressing specific challenges to the emotion recognition aspect of the solution, there are a couple of controversial issues to be mentioned. The ML algorithm is pre-trained with uncontrollable secondary data, prone to biases concerning gender, race, age, and other physical factors. This means that the solution might not apply with the same results universally and a scaled-up industrially implemented solution would require case-specific training with internal company data.

Another challenge is the limited range of emotions typically displayed by workers around robots. Workers often maintain a neutral expression, making it challenging for the system to interpret their emotional states accurately. This poses potential issues in distinguishing between a production-related concern, requiring a robot slowdown or stop, and non-threatening external events. Overcoming such challenges necessitates the development of more advanced context-aware intelligence [24].

While the results are promising, acknowledging the potential reduction in productivity due to the AMR's programming to understand non-verbal cues is crucial. The system's initiation of smooth discourse and occasional waiting for appropriate human responses may lead to decreased productivity. Long-term concerns involve the possibility of employees understanding the impact of their cognitive stress on productivity and potentially altering their non-verbal cues.

Beyond the experiment's scope, the need for total information to inform the system about underlying phenomena in an operator's life is emphasized. This includes human resource information or accounts department data, contributing to the initiation of a gossip protocol [26], between the AMR and the operator, enhancing a more natural discourse.

Addressing general challenges, incorporating offline programming, visualization, simulation, and control features into the project is crucial to overcome issues posed by remote factories and Wi-Fi bandwidth volatility. This approach ensures uninterrupted operations, reducing reliance on real-time data flow susceptible to connectivity limitations. Implementing industrial CPS is advocated for robust production system handling large volumes of data flow efficiently. Other practical implications of these findings suggest the importance of appropriate edge design in deploying sensor networks for effective human-robot interaction in industrial settings.

Considering research points, the integration of technological advances with human needs and worker empowerment is highlighted. In the context of scalability, careful consideration of greenfield and brownfield opportunities is urged, emphasizing alignment with existing platforms to avoid inefficiencies. Lean techniques are recommended before digitalization to eliminate waste, and coordinated initiatives are essential to prevent duplicated efforts.

The importance of economic, social, and environmental sustainability in digitalization efforts is underscored. While digitalization may seem appealing, it should be driven by value creation, aligning with digitalization objectives, organizational competencies, employee competencies, and long-term goals. It is essential to recognize that the successful launch of I5.0 relies heavily on employee engagement and interaction. Without active involvement and participation from employees, the full potential of I5.0 cannot be realized. Organizational culture and mindset play pivotal roles in successful digital transformation, requiring a collaborative approach and effective change management to facilitate the organization's exploration of new possibilities.

Through the proposed integrated solution, comprehensive tracking and tracing of shopfloor key performance indicators (KPIs) becomes feasible. These KPIs might include productivity, resource efficiency, capacity utilization, ergonomic deviations, automation level, workload variation, and employee work-related stresses. Some of these KPIs can be used to determine the environmental impact of the solution. For instance, while the energy consumption of the entire system falls outside the scope of this paper, monitoring and controlling the energy usage of the system are important for evaluating its environmental impact, particularly in terms of SCOPE 2 and 3 emissions. Further research is needed to address this aspect and fill the existing knowledge gap.

Exploring ethics, security, and privacy concerns, data privacy encompasses aspects such as autonomy, the desire for privacy, and data ownership, which vary according to individual customer preferences and business considerations. Privacy measures should encompass data collection, processing, storage, usage, and disposal, ensuring that customer rights are respected throughout the data lifecycle. Both employees and the organizations they belong to should have rights that include transparency, access, objection, restriction of processing, the right to be forgotten, and the right to be informed. The presence of multiple parties involved in data governance introduces further complexity to the equation. It is imperative to acknowledge that another option is just to restrict access of personal data to management and strictly giving access to the employee for their edification and correctly assessing, monitoring, and controlling their own wellbeing.

Possible areas of research include the integration of the AMR with the psychological natural language processing artificial intelligence to maintain a near human natural discourse between the shop-floor worker and the AMR, hence greatly reducing stress levels. Another possible area of research is network agnostics of different domains, dimensions, and functional areas of the organization in developing an intelligent smart production system which is connected, adaptive and prognostic, and can pass recommender systems on all domains with a systematic approach.

7. Summary & Conclusion

In conclusion, this paper presents an end-to-end digital service with two integrated solutions for adapting to and improving the mental condition of employees on the shopfloor, enabling the evaluation of productivity in relation to ergonomic deviations and work-related cognitive stress. It seems possible to utilize the psychological state of the worker with the assistance of modern technology in order to optimize production operations. However, the digitalization process presents its own challenges, both in terms of infrastructure, such as high capital expenditure, latency for scalability, technical competencies gap, limited computational power and an increase in power consumption, and in terms of organizational culture and employee resistance to change.

The experimental results indicate promising avenues for enhancing human-robot collaboration in I5.0, with a focus on reducing cognitive stress and incorporating emotional intelligence into the workplace. The findings underscore the importance of considering various technological and design factors in implementing effective human-robot symbiosis in manufacturing environments.

To ensure robustness and reliability of the production system, the paper suggests the implementation of industrial CPS capable of handling high volumes of real-time data, high velocity, and storage. Additionally, the inclusion of features for off-line programming, visualization, simulation, and control is proposed to address issues related to remote factories and volatile Wi-Fi bandwidth.

The authors emphasize that employee engagement and interaction are vital for the successful launch of I5.0. Organizational culture plays a significant role in digital transformation, necessitating a collaborative mindset and fundamental mindset change within the organization.

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