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Towards Industry 5.0: Augmented Reality Assistance Systems for People-Centred Digitalisation and Smart Manufacturing

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***Abstract*— Although Industry 4.0 has brought multiple positive impacts, the lack of consideration for the human operator in the loop has been a key driver for an 'Industry 5.0' (r)evolution. Human-centricity is a core pillar of Industry 5.0, however, the breadth of emerging Industrial Technologies and methods for worker assistance and their integration in factories' systems are not well understood yet. This paper carries out a systematic review of human-centric manufacturing and discusses the emerging research topics, methods and approaches that are contributing to the next industrial revolution. The key factors on human operator wellbeing, methods and techniques for human-centric manufacturing, and augmented reality assistance systems are analysed. Moreover, the research challenges and gaps are identified, and recommendations on future research directions are provided for the further development of people-centred digitalisation and smart manufacturing research.**

Keywords—Industry 5.0, Human Centric Manufacturing, Augmented Reality, Wellbeing, Ergonomics

I. Introduction

The latest industrial revolution, Industry 4.0 (I4.0), aims to interconnect various manufacturing, management, and supply chain elements. All the interconnected parts of I4.0 are then combined into a Cyber-Physical System (CPS). CPS has enabled the concepts of smart factories, self-organisation, individualisation of design, smart procurement and distribution, and resource efficiency [1].

Although I4.0 benefits economic sustainability, there is an argument that this revolution does not address socially sustainable practices represented through job creation and human operators' wellbeing [2][3].

As a result, an Industry 5.0 (I5.0) vision has been recently established by the European Commission [4], which aims to complement the principles of Industry 4.0 by promoting more human-centric practises, enhancing sustainability (economic, environmental and social) and resilience in the industrial sector (see Fig 1). Academic efforts have been driving the I5.0 vision based on challenges faced by businesses and technological advancements. For instance, the concept of *Operator 4.0* was introduced in [5], where human operators' capabilities are augmented using emerging technologies. Other research topics have been emerging with the aim to embed humans into the thinking of CPS. Relevant work on humans and CPS and automation can be found in [6] and a throughout understanding of industrial assistance systems and the impacts in human-machine interaction is provided in [7].

Within the family of industrial assistance systems (IAS) and immersive technologies, augmented reality (AR) assistance systems (ARAS) represent a core technology that have gained research traction to improve manufacturing practices including operators' training, assembly guidance, maintenance and repair [8][9]. IAS and technologies aim to improve process efficiencies and right first time by enabling operators to perform tasks with minimal effort through physical, sensorial and cognitive assistance [7]. However, there are major gaps in understanding the impact of such technologies on human operator wellbeing factors (HOW), which have been a major barrier to develop effective human-centric manufacturing solutions. Therefore, research into HOW such as cognitive and physical ergonomics and novel monitoring and analysis methods in view of the opportunities brought by ARAS are urgently needed.

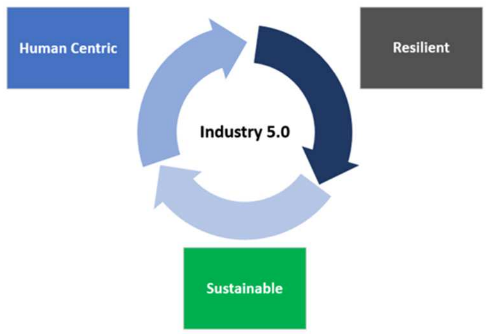

Fig. 1. Pillars of Industry 5.0.

This paper presents vital and fundamental topics for people-centred digitalisation and smart manufacturing in light of human operator wellbeing and technological advances such as augmented reality systems. A systematic review was conducted to select the most relevant publications in human-centric manufacturing, from which topics, methods and concepts towards Industry 5.0 were identified. A review of the existing and emerging research and practises to achieve human-centric manufacturing is conducted, and the research challenges and gaps for future research directions are discussed.

This paper is organised as follows: Section 2 presents the research methodology for the systematic search and analysis, section 3 provides the search results and analysing into the

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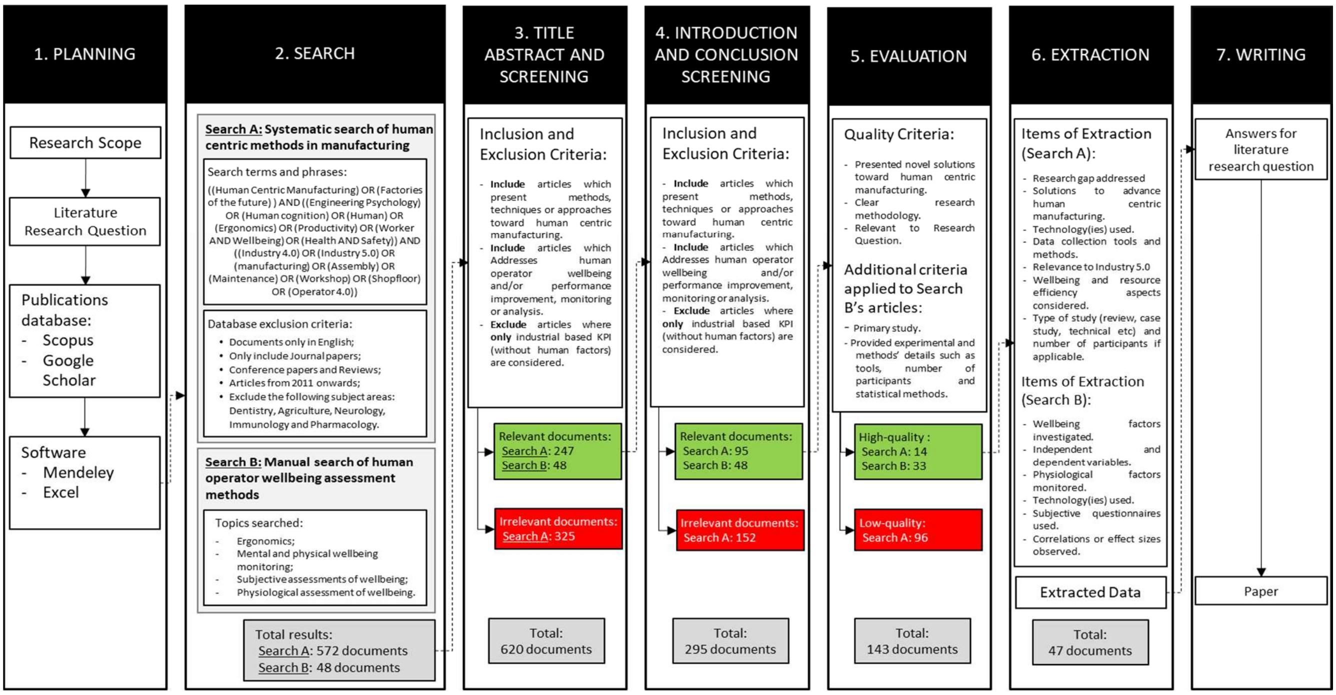

Fig. 2. Details of the research methodology.

key topics identified. The research challenges, gaps and future directions are discussed in Section 4, and, finally the conclusions are given in Section 5.

II. Methodology

This paper uses a systematic review approach to collate the most relevant documents on human-centric manufacturing and human operator wellbeing.

Fig 2 shows the methodology details, including steps, search criteria and search results for each step. The 47 highly relevant documents have been analysed and the results are presented in Section 3.

III. Results and Analysis

An extensive review of the most relevant publications was carried out and the key topics have been identified: human operator wellbeing, methods and techniques for human-centric manufacturing, and AR assistance systems for people-centred digitalisation and smart manufacturing. Each topic is further analysed and discussed.

A. Human operator wellbeing

In [10] and [11], the correlations between the human worker's wellbeing and job performance were investigated and it was observed that wellbeing monitoring holds both economic importance and social benefits. Identifying and monitoring human operator wellbeing factors (HOW) is, therefore, vital to achieving human-centricity, resilience and social sustainability – pillars of I5.0 – for the manufacturing sector.

❖ Musculoskeletal disorders (MSD)

The centre for disease control and prevention describes musculoskeletal disorders (MSDs) as "injuries or disorders of the muscles, nerves, tendons, joints, cartilage, and spinal discs" [12]. Work-related musculoskeletal disorders (WMSD) is the term used to describe MSD if the work condition contributes significantly to the disorder [12]. Relevant tools for assessing WMSD are mainly based on scoring systems. Scoring systems assign a score based on operators' stretching angles, the position of limb body parts, and the load handled. Some of the notable assessment tools include:

- Rapid Upper Limb Assessment (RULA) [13];
- Rapid Entire Body Assessment (REBA) [14]; and,
- Ergonomic Assessment Worksheet (EAWS) [15].

The aforementioned tools often need subject experts to observe operators' movements and assign scores accordingly. Multiple works pursued a real-time scoring system based on established assessment tools to facilitate the implementation of WMSD assessment tools in industry, e.g., manufacturing [16][17][18].

❖ Mental workload (MWL)

The concept of MWL is intertwined with an excepted performance to be achieved on a task under certain conditions [19][20]. Given the established relationship between MWL and performance, a motive for measuring MWL is to predict the operator and system performance by quantifying the mental cost [21]. In the context of Industry 5.0 and human-centric manufacturing, an analysis of MWL is aligned with the need to analyse the impact of emerging technologies, such as collaboration robots and ARAS, to understand their impact on cognitive ergonomics and performance. Furthermore, MWL is a wellbeing hazard which can influence operators' hazard detection [22], decision-making [23] and job dissatisfaction [24]. Multiple monitoring methods of MWL will be presented in this review, including subjective and physiological measurement techniques.

NASA-TLX has been the most used subjective rating method in the context of MWL monitoring for industrial applications; it is also often used to validate physiological measurement tools [25]–[33]. The rating method is a multidimensional subjective scale looking at assessing the following factors: mental demand, physical demand, temporal demand, performance, effort and frustration level [34]. Another relevant subjective scales which have been validated include the Subjective Workload Assessment Technique (SWAT) [35] and the Workload Profile (WP) [36]. SWAT assesses three factors: time load, mental effort load and psychological stress load. This method was created to be sensitive under different conditions of task types [35]. The WP method uses questions for the participants to rate their attentional resources used to complete the task. The attentional resources factors are perceptual, response, spatial, verbal, visual, auditory, manual and speech resources [36].

Other existing techniques estimates the MWL by measuring activity in the participant's brain. For instance, the hemodynamic response measures the oxygenation level in the brain's prefrontal cortex, commonly classified as a direct measurement of MWL [29][37]. Many works have analysed this method's feasibility in the aviation industry context [25], [26], [29], [30], however, to date there's a lack of evidence of testing such technique in manufacturing applications.

Measures of MWL can also be attained using indicators exhibited by the Autonomic Nervous System (ANS) [38]. ANS is a neural component that regulates physiological responses to cognitive phenomena such as emotions. Therefore, in the context of cognitive ergonomics, physiological measures are gateways to the human operator's mental processes and can be indicators of cognitive factors such as MWL, stress or emotions. From the literature, physiological responses related to the ANS were measured to assess human participants' wellbeing; these include Heart Rate (HR), Heart Rate Variability (HRV), Electrodermal Activity (EDA), Pupil Dilation (PD) and Breathing Rate (BR) [38], [39]. The monitoring process of such indicators are considered to be less intrusive than other methods.

HR is defined as the number of heart beats per minute, while HRV is defined as the temporal variation between sequences of consecutive heart beats. ANS indicators HR and HRV can be measured using the electrocardiogram (ECG) or photoplethysmography (PPG) [40], [41]. The latter provides a low-cost and compact solution, and is therefore feasible for non-intrusive monitoring of HR and HRV using wearables [42]–[44].

Literature indicates that HR and HRV are sensitive to MWL and eligible to be deployed in modern manufacturing context [32], [45], [46]. Furthermore, HRV has the potential to differentiate between different factors of cognitive wellbeing, such as vigilance [47], habituation [45] and stress [48]. Electrodermal activity (EDA), or galvanic skin resistance, has been used to measure cognitive stress and emotions [49], [50]. EDA is a good indicator of human operator factors such as vigilance [47] and arousal [50], however, the research works presented in [27], [47], [50] highlights that there's insufficient evidence that EDA is sensitive to MWL. The ANS indicator BR has shown to be a good indicator for human operator MWL [25], [28], [38].

Pupil dilation (PD), another indicator of ANS, has been one of the oldest and most established methods for measuring cognitive load according to the literature [51]–[53]. From a practical perspective, pupil measurement requires direct eye measurements; a commercial pupilometer uses an infrared wavelength interferometer, such a device must be physically placed on the participant's eye [54]. Augmented and Virtual (AR and VR, respectively) devices represent a potential solution that enable the measurement of PD using built-in cameras [55], [56]. For many scenarios, PD measurements can be intrusive, especially if an operator is working on a physical object during assembly or maintenance tasks in manufacturing.

❖ User and technology acceptance

User and technology acceptance has been a research interest given that it affects the success of digitalisation in manufacturing and directly impacts on company's return on investment in new technologies.

In the context of emerging and existing technologies for Industry 5.0, studies on the acceptance and user perception of relevant technologies were conducted to assess their impact on wellbeing and resource efficiency. Many of the works analysing technology acceptance and trust were analysing the perception of human workers towards robots for 'Human Robot Collaboration' scenarios [9], [57], [58]. Analysis methods such as Technology Acceptance Model (TAM and TAM3) aim to explain the user acceptance processes and assess the likelihood of a product being accepted by its users [59]. In [9], the relationships between cognitive load (such as MWL) and the users' perception of cobots were investigated, and they observed that the perception of cobots is related to indicators of MWL, such as physiological measurements. Nevertheless, to date, there are major gaps in the literature on exploiting the capabilities of AR assistance systems (ARAS) and other emerging technologies, such as digital twins, AI and sensing technologies, to enhance user acceptance and improve human operator wellbeing.

B. Methods and techniques for human-centric manufacturing

This section reviews the literature on concepts, approaches, methods and techniques aimed at achieving the Industry 5.0 vision.

❖ Operator 4.0 (connected worker)

Human-machine collaboration is an important topic for the roadmap toward Industry 5.0 and the implementation of human-centric manufacturing systems. Some of the early literature delving in the application of human-machine collaboration specified its importance for decision making and planning [60] Another major challenge for an effective human-machine collaboration in Industry 5.0, is the ability to create an adaptive interaction. This challenge has been addressed in [61] where a human-in-the-loop system was designed to support teachers by using machine learning models and Natural Language Processing. A framework for the implementation of human-machine collaboration in manufacturing is suggested through 'Operator 4.0'.

The concept 'Operator 4.0' has been proposed to enhance the existing framework of Industry 4.0 by utilising CPS to include human operators in the loop [5]. To achieve 'Operator 4.0', concepts such as Human Cyber-Physical systems (H-CPS), Adaptive Automation (AA) and Human in the loop (HITL) were introduced. Human Cyber-Physical systems (H-CPS) aim to embed the operators in the CPS in a manner which goes beyond just improving productivity metrics and aims to improve the worker's physical and cognitive wellbeing. AA and HITL rely on a closed loop system which can adjust the level of automation and avoid assigning repetitive tasks to humans.

Nevertheless, the Operator 4.0 is still a conceptual framework with more work and research needed to address technical, methodological, ethical and legal challenges surrounding its implementation.

❖ Use of human operator wellbeing data

Human operator wellbeing (HOW) data provide the vital resource to monitor, analyse and, ultimately, improve human operators' wellbeing and ergonomics. To understand how wellbeing factors and monitored data fit into an industrial context, relevant literature showing techniques and strategies to measure HOW indicators were presented in previous sections.

Data gathered from sensors (such as ANS indicators) often consist of numerical values and do not directly inform managers about the mental state of human workers. Consequently, there's a need to utilise methods to translate that data into meaningful information. For instance, the technique user experience index (UXI) has been developed to calculate the user experience [62]. UXI represents a multidimensional user experience analysis, based on four indicators: postural data score (physical workload, e.g., REBA data), physiological/cognitive data (e.g., mental workload, e.g., HR and PD data), and performance (e.g. completion times) and perceived workload (subjective assessment, e.g., NASA-TLX questionnaire). The four indicators and the baseline measurements (the measurements during resting periods for the physiological parameters, expert parameters for performance or the minimum REBA score for postural data) are used to calculate the UXI. The UXI technique was tested in industrial scenarios [63], [64] and has been shown to be a supportive tool for managers to assess human operators' comfort levels. However, it requires large amounts of measurements and data, which can be time and resource-consuming.

More recently, the concept of adaptive automation [5] has been developed and aims at deploying physiological data to improve human-centricity in manufacturing. Furthermore, such data is used to close the loop between the human and the machine, to maintain the human operator's cognitive indicators within safe and comfortable levels. A similar approach was proposed using a flight simulator, where users' EDA, HR and HRV indicators were measured and used for automated decision-making [27], [50]. Another relevant approach utilised experimentally measured results for human wellbeing in clustering analysis for human-robot interaction analysis in lab environment [9]. In addition, an H-CPS system architecture was presented to demonstrate how wellbeing data can be used for attaining HITL by scheduling tasks according to the operator's wellbeing data [63].

To date, the literature has revealed a few concepts for adaptive automation. However, an adaptive automation system has not been fully tested and implemented in a real-world environment where the wellbeing indicators are in a closed loop for CPS decision-making or the interface system.

C. AR assistance systems for people-centred digitalisation and smart manufacturing

Augmented reality (AR) technologies are advancing the integration of humans, machines and systems, and becoming a key technology advancing human-centric manufacturing concepts such as H-CPS and HITL.

The value of AR assistance systems (ARAS) in manufacturing applications relies on its software and hardware capabilities and system design features to assist workers executing tasks (e.g., assembly, maintenance, repair). ARAS can be categorised based on the different types of technologies as follows:

(a) Projection-based (or spatial) AR: this technology is often used in industry with industrial operator guidance systems such as ARKITE [65] or Light Guide System [66]. Those systems consist of infrared, RGB and depth cameras (to detect the progression of the work task, quality criteria, etc.) a projector (to provide contextualised projected visual instructions, e.g., onto a workbench) and a pc unit running an intelligent manufacturing operations management software.

(b) Hand Held Display (HHD): the basic principle of HHD AR is to use hardware such as smartphones or tablets to view instructions which are overlayed on the real world, as viewed from an HHD screen. It is a relatively cheap option, given the abundance of AR-capable devices. However, there are limitations given that the hand of the user is occupied with handling the device.

(c) Head Mounted Display (HMD): this technology is used for both virtual reality (VR) and AR. AR see-through HMD can be used while offering the capabilities of spatial-AR and HHD. A challenge with HMD and HHD is establishing the reference frame. One solution is to use marker-based detection to fix the frame of reference on the workstation [67], however, it limits freedom of movement.

In the literature, most authors mainly focus on quantifying the process performance measures, in which productivity metrics (i.e., completion times and error rate) are predominant [68]–[71]. Literature, such as [71] suggests that the use of ARAS for various manufacturing tasks reduces the mental workload in comparison to the use of traditional methods such as on-screen instructions or paper manuals. In addition, the use of subjective questionnaires, such as the NASA-TLX, has been the most common method of assessing operator wellbeing MWL. Another study [72] integrated a human posture monitoring technique to assess WMSD risks of workers while using ARAS.

Other prominent capabilities of ARAS have been collated based on the literature findings, authors' experiences, and communications with technology suppliers, and are highlighted as follows:

- Ability to provide contextualised and timely information to perform tasks (e.g., assembly maintenance and repair);
- Ability to provide visual instructions (e.g., pick and put-by-light, video and audio instructions) which are highly flexible and adaptable;
- In-process real-time adjustments using computer vision to validate the correctness of human actions and track performance, parts, critical to quality and safety aspects (features such as snapshots, counters, id reader, integration with other sensors and equipment);
- Ability to integrate and/or communicate with other devices (software and hardware) such as external sensors, machines, robots, etc., and utilise the information to adapt the type of guidance (and information) provided;

- Ability to adapt to operator's skill and experience levels and provide adequate work instructions, and
- Ability to integrate with manufacturing managerial systems (e.g., product lifecycle management, PLM, manufacturing execution systems, MES, and enterprise resources planning, ERP).

Such capabilities could help manufacturers to overcome major challenges such as human errors, low productivity, right-first-time, up- and re-skilling with improved learning/teaching capabilities and flexibility, especially, in the context of mass customisation [64], [73], [74]. However, the great potential that such capabilities bring is far from being fully exploited from the perspective of people-centred productivity (PCP), human operator wellbeing (HOW), inclusivity, diversity and equity (EDI) in manufacturing.

To date, there are major gaps in the literature on methods and approaches to exploit AR systems' capabilities and emerging sensing and monitoring technologies to capture accurate data and develop data-driven systems considering factors beyond process performance, i.e., HOW factors (cognitive, physical, feelings and emotions), and beyond such as inclusivity and equity factors [7].

IV. Discussions: Challenges, Gaps and Future Research Directions

This section discusses the research challenges, gaps and future research directions based on the results and analysis presented in the previous section.

Despite the potential of ARAS to advance human-centric and smart manufacturing, the literature review carried out in this paper highlights major challenges and research gaps that require urgent attention.

Research challenges:

- The complexity of mapping and understanding the relationships impacting human operator wellbeing and performance and what to do with the data;
- Effectively deploying human operator wellbeing data for the goal of improving the human operator's wellbeing and performance);
- Developing cross-disciplinary research approaches that capture the multidisciplinary nature of the challenges in people-centred digitalisation and smart manufacturing.

Research gaps**:**

- Scarcity of studies understanding the correlations between human operator wellbeing when using industrial assistance systems (e.g., ARAS) and how to utilise the information;
- Lack of experimental evidence on the effects of human operator wellbeing and user acceptance when using ARAS;
- Lack of literature investigating the effects of human factors and ARAS beyond traditional ergonomic aspects, such as skill levels, trust, values, psychological capital, feelings and emotions, etc.;
- Lack of research addressing the limitations of current human-centric approaches: adaptive automation (AA), human-in-the-loop (HITL) and human-cyber physical systems (H-CPS);
- Lack of literature focusing on advancing approaches, techniques and tools to improve capturing, monitoring and deploying human operator wellbeing data.

It is important to note that the aforementioned research gaps spotlight the need for cross-disciplinary research approaches to deal with the multidisciplinary elements of the challenges. Consequently, the development of research on people-centred digitalisation and smart manufacturing must consider perspectives, methods and tools from multiple disciplines, beyond engineering and manufacturing, including psychology, behaviour, dance (or movement), management, legal and computer sciences.

Based on the above, the following future research directions are recommended:

- Cross- and trans-disciplinary approaches to human-centric manufacturing research;
- People-centred algorithms for cyber-physical systems and human-centric manufacturing, human-centred algorithm design (HCAD);
- Human-centred KPIs (advanced performance metrics);
- Human digital twins (HDT) and ARAS for enhanced monitoring and optimisation of operator performance and wellbeing.

V. Conclusion

This paper implemented a systematic review approach to gather the most relevant papers in people-centred digitalisation and smart manufacturing in light of the technological advances in augmented reality assistance systems (ARAS). The systematic review approach included automated and manual search methods to select the most relevant publications and extract the latest methods, techniques and concepts towards Industry 5.0, focusing on human operator wellbeing and AR technologies.

The results highlighted the following core topics of investigation: i. human operator wellbeing (HOW) factors; ii. techniques and methods for human-centric manufacturing; and, iii. AR assistance systems for people-centred digitalisation and smart manufacturing. Furthermore, the analysis of the results illustrates that understanding, monitoring and analysing human operator wellbeing (and ergonomic factors) represent a crucial aspect and play an important role in the future industrial evolutions, I5.0. However, there remains major challenges and gaps in the literature related to human operator wellbeing and human-centric manufacturing research, with key topics requiring urgent attention, to include:

- more empirical research is urgently needed to better understand HOW and traditional ergonomic factors when using ARAS;
- more cross-disciplinary research is needed to address the limitations and opportunities of advancing HOW metrics to achieve concepts such as 'Operator 4.0'.

To conclude, future research should aim to test how emerging technologies such as AR could be paired with

HOW factors monitoring to realise concepts such as operator 4.0.

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