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INTEGRATING COMPUTER-AIDED ENGINEERING AND COMPUTER VISION FOR HUMAN-CENTRED WORKSPACE DESIGN IN INDUSTRY 5.0: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Industry 4.0 has morphed into Industry 5.0 and shifted the focus from a technology-only approach to manufacturing to one that considers human-centricity, sustainability and resilience. This is transforming the design of manufacturing work spaces in the ways engineers can capture the physical workspace but can also capture the posture, movement and capabilities of the people who work within the space. This picture can be broken down into several components: Computer-Aided Engineering (CAE), Finite Element Analysis (FEA), Digital Human Modelling (DHM), computer vision, ergonomic assessment, human-robot collaboration (HRC) and Human Digital Twins (HDTs) all play a part in this. The aim of this review is to analyze the current state of the integration and contribution of these technologies to human-centred workspace design in the context of Industry 5.0, according to the PRISMA 2020 guidelines, 39 peer-reviewed studies published since 2016 were synthesized. As it becomes clear: CAE and DHM can be used to test and fine-tune a workspace before it is constructed, and computer vision enables the actual way people move and hold themselves in the shop to be captured. When combined, the two allow for automated ergonomic risk assessment, more optimised work stations, HRC customized to the individual and continuous real-time monitoring, while HDTs take this one step further by connecting a physical worker to a virtual worker, that informs manufacturing decisions. Real obstacles remain. Some of the remaining open questions are how to achieve interoperability, how to validate computer vision, how to maintain privacy, how to process data in real-time, and how to meaningfully embed the human body and mind in engineering models, which are still confronted by issues of accuracy, occlusion, and placement of the camera. The evidence from the emerging industrial economies is particularly light, where the adoption of digitalisation is patchy and resources are limited. The review suggests an integrated eight-layer structure in which the CAE, computer vision, HDTs and statistically based optimisation will combine in closed loop to continually modify workspaces to match the people using them, as Industry 5.0 demands human-centricity.

Keywords: Industry 5.0; Human-Centred Design; Computer-Aided Engineering; Computer Vision; Digital Human Modelling; Human Digital Twin; Ergonomics; Systematic Literature Review

1 INTRODUCTION

Manufacturing has changed dramatically as production systems have moved from traditional set-ups towards Industry 4.0. That shift introduced the concept of cyber-physical systems, the Internet of Things, artificial intelligence, robotics, digital twins and advanced data analytics to the factory, and for the most part the spotlight was on automation, connectivity, productivity and optimisation. However, the adoption has not been consistent.

Despite the positive outcomes of data-driven tools in condition monitoring and predictive maintenance in developed economies (Mashava et al., 2026; Senda et al., 2026), manufacturers in developing economies like Zimbabwe are experiencing infrastructure deficits and a lack of skills and organisational commitment that impede the adoption of Industry 4.0 technologies (Muhla et al., 2025a). However, as manufacturing processes become increasingly technologically complex, some doubt has been expressed as to how workers fit into this complex mix – in terms of wellbeing, skills required by workers, safety, and how humans should relate to increasingly intelligent machines (Kadir, Broberg and Conceição, 2019; Reiman et al., 2021). These questions have led to the creation of Industry 5.0.

It is not about replacing Industry 4.0, but it is about adding to it, with emphasis on human-centricity, sustainability and resilience, along with advances in technology. Lu et al. (2022) name one of the main fronts that Industry 5.0 is heading towards as human-centric manufacturing, and Zhang et al. (2023) classify human-centric smart manufacturing as a new area of research. In a similar vein, Li et al. (2023) state that comprehending the changing role of the human plays a core part in the practical implementation of human-centric manufacturing, and expands on the previous Operator 4.0 vision of socially sustainable factories (Romero, Stahre and Taisch, 2020). Organisational agility – the ability to rapidly reconfigure business operations in rapidly changing markets – is a key factor for resilience and is also found to be limited in many Zimbabwean manufacturing firms (Muhla et al., 2024). This human-focused approach to manufacturing shifts the focus of workspace design. A

workstation is never merely machines, tools and materials located in space, but a space where people work with machines, robots, information systems and the overall production process. Poorly designed can lead to uncomfortable movements, excessive physical effort, repetitive strain, fatigue, and ultimately to work-related musculoskeletal disorders (WMSDs). Safety, too, is affected: Muhla et al. (2025b) in a mixed-methods study of manufacturing enterprises in Zimbabwe, showed ergonomic design to be a large contributor of workplace accidents and demonstrated that human factors engineering interventions have a positive impact on reducing workplace accidents. To properly design a workspace, therefore, engineering requirements must be taken into consideration along with human factors, not separately (Nguyen Ngoc, Lasa and Iriarte, 2022). One place to begin is Computer-Aided Engineering (CAE). It allows engineers to model, simulate and test engineering systems without having to build them physically.

For stress-strain analysis, deformation and mechanical behaviour of structures and components, finite element analysis (FEA) can be used, as in the case of the vertical-axis wind turbine (VAWT) designed for highway slipstream energy harvesting illustrated by Muyambo et al. (2025), where FEA was applied to the same virtual-prototyping logic for the application of the wind turbine to the flow problem. However, CAE can be applied directly to human-centred ends as well: Tandi et al. (2025) designed and analysed a passive upper-limb exoskeleton to assist construction workers in overhead loading by using a SolidWorks–ANSYS workflow. Conventional CAE, on the other hand, doesn't capture the entire picture of how humans, machines and the work environment interact with each other. Digital Human Modelling (DHM) helps to fill in that gap. DHM maps human body size, posture, reach and motion to a virtual world, linking the type of simulation engineers work with, to the requirements of human centred design. For an overview of the importance of digital human models for human-centred design in general, see Mochimaru (2017), and in the context of occupational safety and health in a manufacturing environment, Schall, Fethke and Roemig (2018).

Grobelny and Michalski (2020) go even further: They show how DHM can help prevent WMSDs before they even become a problem. In parallel, computer vision has given the opportunity to understand the work that is actually done. In contrast to manual ergonomic observation or wearable sensor, computer vision systems can analyze the posture and movements from images and video. Massiris Fernández et al. (2020) has, for example, developed a computer vision and machine learning system for automated Rapid Upper Limb Assessment (RULA) and demonstrated that in principle, ergonomic risk can be measured automatically from video rather than by hand by an observer going through a checklist.

Digital twins, and Human Digital Twins (HDTs) in particular, are the element that brings the physical and virtual together and that makes the connection with Industry 5.0 most obvious. HDTs are a major technology to implement human-centricity in Industry 5.0, presented by Wang et al. (2024) as digitized human being that links individual characteristics with the design and performance of manufacturing systems. Although Smart Manufacturing has advanced, the design of manufacturing workplaces is still often divided into two worlds: Engineering simulation and Human factors assessment. Traditional CAE and FEA are appropriate for analysing real parts or structures but are not designed to much about a worker's posture, fatigue, movement or ergonomic risk. This type of data is just too much for

such tools. Traditionally, ergonomic assessment has been conducted by observation, typically using RULA (McAtamney and Corlett, 1993), REBA (Hignett and McAtamney, 2000) and OWAS (Karhu, Kansil and Kuorinka, 1977).

They are valuable and proven tools, but using them manually is time-consuming and partially subjective, and, since an assessor can only see a worker at certain times, he or she will only be able to get a glimpse of the worker's activity. Computer vision can do something about this, as it can in principle observe a worker continuously, instead of taking snapshots. This is demonstrated in practice by Massiris Fernández et al. (2020), and later by Nayak and Kim (2021) who automated the entire RULA scoring process. Despite these advantages, computer vision systems present several challenges, such as occlusion, poor or variable lighting conditions, camera positioning and camera orientation; and validation in real factories is still in its early stages (Agostinelli et al., 2024). There is another layer: It's not just whether or not the technology works, it's what happens when it does. Once a worker has been identified as having an awkward posture, the next step is to influence the design of the workstation that is causing the posture. The relationship between assessment and design remains still underdeveloped, and is weakest in environments with low resources and where digital infrastructure is in its infancy (Muhla et al., 2025a).

The goal of this systematic review is to investigate the current state of the art of the research on the integration of CAE and computer vision for human-centred workspace design, as well as what the technologies can contribute to the human-centric manufacturing of Industry 5.0. It serves three purposes: It classifies the literature in the technology field by applying the PRISMA approach, it compares critical the points in which the studies agree and it compares the points in which they differ, and it provides an integrated framework with 8 layers that connects sensing, human representation, ergonomic assessment and statistically grounded optimisation of studies in a closed loop.

Research Objectives

The study sets out to:

- Trace and examine how CAE and DHM have developed for human-centred workspace design since 2016.
- Review how computer vision and machine learning have been applied to assessing human posture and ergonomic risk.
- Investigate the part that human-robot collaboration plays in human-centred manufacturing environments.
- Examine the emergence of Human Digital Twins as a way of linking physical workers to virtual manufacturing environments.
- Identify the main challenges and limitations involved in integrating CAE, computer vision and Industry 5.0 technologies.
- Identify gaps in the current research and propose directions for future, more integrated approaches to human-centred workspace design.

2 BACKGROUND AND THEORETICAL FOUNDATION

2.1 Computer-aided engineering and digital human modelling

CAE tests designs virtually, and DHM brings a worker into the simulation to evaluate fit, reach, and movement and ergonomic risk prior to the construction of a workstation (Mochimaru, 2017). The analysis of operator position and workload data collected during virtual assembly planning can be used to score the postural risk and metabolic load at the design stage (Alkan et al., 2016) and DHM can be used to identify potential muscle and joint injuries in advance before they occur (Grobelny and Michalski, 2020). Structural CAE can contribute where the load case comes from the human task: for the passive exoskeleton developed by Tandi et al. (2025) three configurations were modelled and analysed in ANSYS, with a carbon-fibre design selected due to a factor of safety of 2.1 (versus 1.38 for nylon). But simplified human models can not describe the full spectrum of human motion and interaction models are too complicated and not sufficiently well validated, therefore DHM should be accompanied by other technologies (Wolf, Miehl and Wartzack, 2020).

2.2 Computer vision for ergonomic assessment

Computer vision and machine learning were used to estimate RULA scores from images or video, which allowed more frequent digital RULA assessments (Massiris Fernández et al., 2020), and more recently, the entire RULA scoring process was automated (Nayak and Kim, 2021). The accuracy of these tools has been tested in real manufacturing environment and has been shown to be dependent on the camera positioning, lighting conditions, occlusions and workstation layout (Agostinelli et al., 2024). Inertial motion capture does not need to look to an object, but does require workers to wear equipment (Fletcher, Johnson and Thrower, 2018). These human-centred sensing applications outside the factory also highlight the same point: A low-cost smart wheelchair using ultrasonic sensing and speech and joystick control was able to prevent collisions within a 50 cm radius with reliable performance, but the voice-recognition component proved to

be prone to errors (Munotyaani et al., 2026), reminding us that the perception components should be validated independently before being trusted to make safety-critical decisions. It is therefore important to approach computer vision as a continuous monitoring input into the ergonomic expert and broader decision making system instead of replacing it.

2.3 Human-robot collaboration

Industry 5.0 is an alliance between humans, with their ability to think, adapt and solve problems, and robots, with their ability to be precise and to work repeatedly and in hazardous environments. Cobot safety and ergonomics (Gualtieri et al., 2021) and the design of HRC workspaces (Simões et al., 2022) are reviewed, and studies of demanding power-tool tasks (Kim et al., 2021) and job rotation on assembly lines (Dalle Mura and Dini, 2022) illustrate how HRC can reduce physical strain. When complete robotic collaboration is not feasible, passive wearable devices provide an alternative, more affordable pathway toward a similar objective (Tandi et al., 2025). These benefits rely on safe layouts and utilization of tasks, not just adding robots.

2.4 Digital twins and human digital twins

A digital twin is an ongoing link between a physical system and a virtual system. In the manufacturing industry, it can integrate information from the processes, workstations, equipment and employees, enabling engineers to monitor and assess changes (Ramasubramanian et al., 2022). Building safety-aware twins (Choi et al., 2022; Gallala et al., 2022; Li, C. et al., 2022; Yi et al., 2022), HRC cell reconstruction (Li, C. et al., 2022; Yi et al., 2022), modeling the operator state (Shi et al., 2022), and reasoning the state on the shop floor (Li, H. et al., 2022; Wang, H. et al. 2023; 2024) are all emerging themes for vision-based twins, mixed-reality twins, cognitive twins and ontology-driven twins, respectively.

Those human data representation are starting to become reusable in different applications with the introduction of IIoT platforms (Montini et al., 2022). Architectures from the maintenance domain illustrate how the sensing to decision chain can be constructed in resource constrained environments. Mashava et al. (2026) connected infrared temperature sensors, flow sensors and conductivity sensors to a PLC and OPC server and used a multi-agent platform implementing FIPA to detect and notify faults in real time on induction furnaces and Senda et al. (2026) used a RF classifier over thirteen years of operation to optimise the PM strategy of a thermal power station boiler.

While these studies are about equipment and not workers, the sensing, reasoning and notification schemas are very much applicable to a human-aware twin. This linkage, in conjunction with worker sensing and HDT/CAE, can help to create a feedback loop between the physical workspace and the simulation/decision support. The people represented by the HDTs are linked to their characteristics and the design and performance of manufacturing systems (Wang, B. et al., 2024). An HDT can track posture, movement, fatigue, workload, and worker-robot interaction over time (Miller and Spatz, 2022; He et al., 2024), and the components of the HDT and its interfaces are starting to be formalized (Gaffinet, Naudet and Panetto, 2025).

The concept has been extended to cognitive and information-based work (Mordaschew, Latos and Tackenberg, 2025) and to vision-based fatigue estimation of both physical and cognitive fatigue (Chand, Zheng and Lu, 2024) and task planning of collaborative assembly that takes fatigue into account (You et al., 2025). This is a promising way in which computer vision and CAE can be integrated, but needs tests to be carried out in the real world.

2.5 Industry 5.0 and human-centred manufacturing

While Industry 4.0 focuses on increasing automation and productivity, Industry 5.0 takes a new approach, moving away from automation and productivity and towards human-centricity, sustainability, the resilience of the system, and the wellbeing of workers and human-machine collaboration. Human-centric manufacturing is understood as a key direction and is supported by technologies like digital twins, augmented reality and intelligent systems (Zhang et al., 2023), and approaches that consider humans and systems as co-evolving (Li, X. et al., 2023; Wan and Leirmo, 2023). What actually happens to make the 'human' part of this agenda 'human', however, is uneven (Briken et al., 2023). The sustainability pillar also extends to the process level: A multi-objective optimisation of cutting and honing parameters has demonstrated that it is possible to optimise the machining energy at the planning stage without compromising the surface quality (Tayisepi et al., 2023; 2024). Therefore, the design of work areas should take into account the interworking of people and technology in order to ensure protection and sustainability, as well as production objectives.

3 METHODOLOGY AND SEARCH STRATEGY

This study was based on a systematic literature review (SLR) that followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021). A search protocol was developed that can be reproduced and is explicit to minimize selection bias and enable other researchers to extract the same corpus.

3.1 Information Sources and Search Strategy

An exhaustive electronic search was conducted in multidisciplinary and domain-specific resources and databases related to design engineering, computer science, and occupational ergonomics: Taylor & Francis Online, IEEE Xplore Digital Library, Google Scholar and CORE (Connecting Repositories). Papers published between January 2016 and the last search in 2026 were collected, which was designed to reflect the fast evolution of real-time digital twin architectures and markerless, edge-computing vision algorithms. Boolean operators, along with controlled technical vocabulary, were used on the title, abstract and keyword fields as follows: (“computer-aided engineering” OR CAE OR “digital twin” OR CAD) AND (“computer vision” OR “pose estimation” OR “object detection”) AND (“human-centred” OR ergonomics OR “workspace design” OR “worker safety”).

3.2 Eligibility Criteria and Screening Protocol

Studies met the inclusion criteria if they used computer vision or human motion sensing with CAD/CAE or simulation, and discussed the human aspect of manufacturing, such as ergonomics, fatigue or safety. Studies without simulation component or design and studies that focused on robotics with no worker in the loop, as well as patent or company report type studies, were not included. The titles and abstracts were primary screened, and the full texts were then assessed. Where there was any disagreement between reviewers, it was discussed until consensus was reached. Following screening, 39 studies were included in the synthesis process (Figure 1).

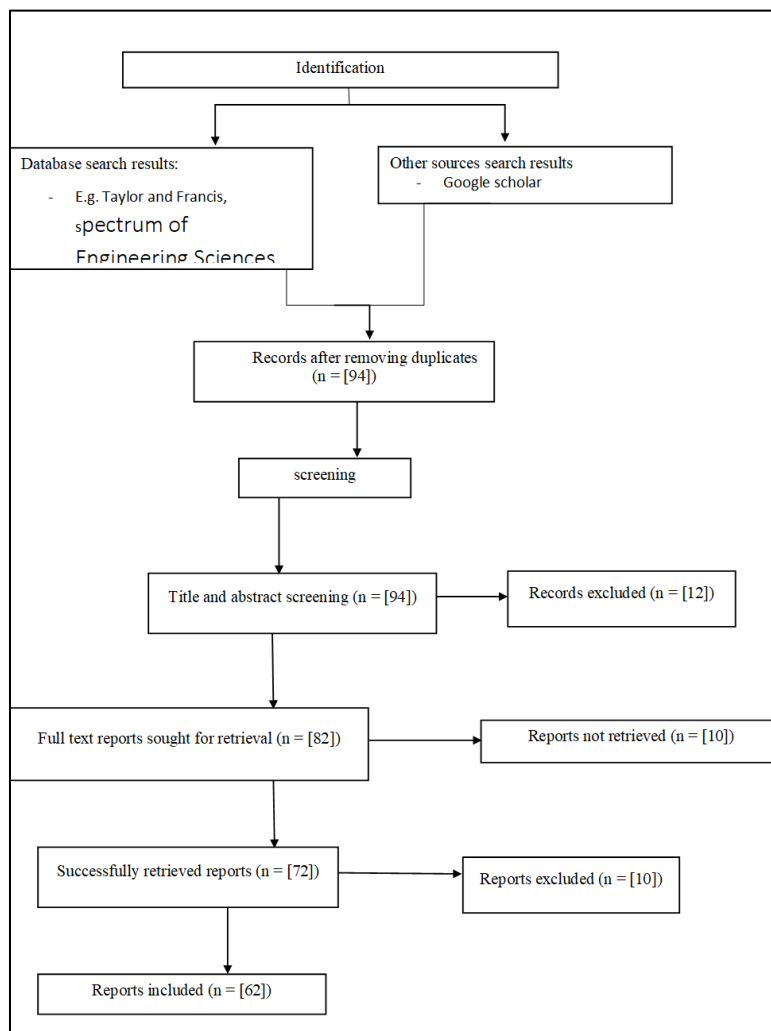


Figure 1: PRISMA 2020 flow diagram of study identification, screening and inclusion. Adapted from Page et al. (2021).

4 PROPOSED INTEGRATED FRAMEWORK

Drawing on the literature, this review proposes an eight-layer framework for human-centred workspace design (Table 1). The layers are grouped into four functional pairs that together form a closed loop from the physical workspace to its redesign.

Table 1: Proposed eight-layer integrated framework for human-centred workspace design

Layer	System Component	Primary Technical Function
1-2	Physical Workspace & Data Acquisition	Real-time CV and sensor tracking of worker posture and machinery.
3-4	Human Representation & CAE Simulation	Live feeding of pose data into DHM/FEA engines to simulate layout reach.
5-6	Ergonomic Assessment & Intelligent Decision	Automated RULA/REBA scoring via AI to flag fatigue and physical risk.
7-8	Optimization, Adaptation & Closed-Loop Feedback	Dynamically adjusting cobot tasks or cell geometries based on live tracking.

The optimisation and adaptation layers (7-8) do not have to wait for new methods. Distributed search on optimization tasks of a workstation's design space is possible using a set of design of experiments (DOE) methods already used in process optimisation. In particular, Taguchi orthogonal arrays (OAs) have been used in conjunction with analysis of variance (ANOVA) and grey relational analysis (GRA), which has helped to resolve conflicting multi-response optima in injection moulding (Mapindu et al., 2026a), CNC milling (Mapindu et al., 2026b) and fused deposition modelling (Mapindu et al., 2026c), weld strength optimization (Mapindu et al., 2026d) while regression-based predictive modelling has been applied as a guide for process-system design in edible-oil refining (Jansen et al., 2025). Another optimization study used Taguchi to investigate the effects of lubricant fat content on drawn copper wire using Lean principles (Chiduwa, et al., 2013). If, instead of cycle time and quality, the ergonomic risk scores generated in layers 5–6 were considered as additional results, it would allow the same machinery to make a trade-off between human and production requirements when the workstation is reconfigured, evaluating each of the possible reconfiguration layouts virtually first, before reconfiguration is actually performed in layers 3–4. The second area is the reconfiguration that is then quickly followed by the fabrication of the re-designed fixtures, jigs and hand tools using optimised additive manufacturing.

4.1 Classification and Taxonomy

All 39 studies that passed the screening were categorized according to the main technology field and by type of contribution and by year of publication. One study was assigned one category per dimension based on the goal and primary contribution of the study and domains were aligned to the eight-layer framework (Table 2). The synthesis reveals a literature that is focused on the production of digital twins and Industry 5.0, with few connections between DHM and vision-based assessment and less field validation for the newer areas.

Table 2: Primary classification of the reviewed studies by technology domain (n = 39)

Domain	Defining focus	Studies	Representative studies	Layers
CAE and digital human modelling	Virtual manikins and simulation used to test workstation posture, reach and risk before construction	5 (12.8%)	Mochimaru (2017); Schall, Fethke and Roemig (2018); Grobelny and Michalski (2020); Wolf, Miehl and Wartzack (2020)	3–4
Vision and sensor-based ergonomic assessment	Automated capture and scoring of posture (RULA-type logic) from video or inertial data	4 (10.3%)	Fletcher, Johnson and Thrower (2018); Massiris Fernández et al. (2020); Agostinelli et al. (2024)	2, 5
Human-robot collaboration	Collaborative workspace design, safety and ergonomics-driven task allocation	4 (10.3%)	Gualtieri, Rauch and Vidoni (2021); Kim et al. (2021); Simões et al. (2022)	1, 7

Digital twins for human-aware manufacturing	Twins of cells, lines and workstations that include the operator, safety or interaction	10 (25.6%)	Ramasubramanian et al. (2022); Wang, H. et al. (2024); Montini et al. (2022)	6, 8
Human digital twins	Digital representations of individual workers, updated with posture, fatigue and workload	7 (17.9%)	Miller and Spatz (2022); He et al. (2024); Wang, B. et al. (2024)	3, 8
Industry 5.0 and human-centric manufacturing	Conceptual grounding, reviews and scoping studies of human-centricity	9 (23.1%)	Lu et al. (2022); Li et al. (2023); Wan and Leirno (2023); Zhang et al. (2023)	All
Total		39 (100%)		

4.2 Critical Analysis of the Literature

The 39 studies varied in design, task, measures and setting, therefore findings were synthesized narratively and not pooled. Within each technology area comparisons were drawn between real-workstation or industrial-data validation and between the various areas of the review framework. Conceptual proposals and prototypes received less weight than real-workstation or industrial data validation.

4.3 Main areas of agreement and debate

Human-centricity is considered as the key characteristic of transition to Industry 5.0 (Lu et al., 2022; Zhang et al., 2023), the ability to automatically assess posture from video (Massiris Fernández et al., 2020; Nayak and Kim, 2021) and the potential of collaborative robots to alleviate physical strain (Kim et al., 2021; Dalle Mura and Dini, 2022). However, design decisions can impact the benefits. In some workstation scenarios, simplified manikins can estimate risk well (Grobelyny and Michalski, 2020) and static human models might not be able to represent dynamic interaction (Wolf, Miehl and Wartzack, 2020). Thus, the level of simplification that is acceptable will vary with the job and no common rule can be found in the literature.

Table 3: Comparative synthesis of the reviewed literature by technology domain

Domain	Where studies agree	Where they diverge or fall short	Evidence maturity
CAE and digital human modelling	Virtual testing catches ergonomic problems before a workstation is built	Simplified, static interaction models; no shared rule for how much simplification is acceptable; structural FEA barely represented	Established, with applied cases
Vision and sensor-based ergonomic assessment	Posture scoring can be automated from video	Occlusion, lighting and camera placement; few real-factory validations; vision and inertial capture not compared directly	Developing; field validation beginning
Human-robot collaboration	Robots can act as an ergonomic measure	Safety, task allocation and layout decide whether the benefit is realised	Developing; reviews and design studies
Digital twins for human-aware manufacturing	Linking physical and virtual systems supports safety and monitoring	Mostly prototypes and platforms; little evidence of deployment	Emerging; method-heavy
Human digital twins	A worker-level twin is the logical step beyond digital human models	Definitions and architectures not yet standardised	Emerging; mostly conceptual
Industry 5.0 and human-centric manufacturing	Human-centricity is the defining shift from Industry 4.0	Ethical and performance framings differ; human-centred claims rarely tested empirically	Broad consensus; largely conceptual and review-based

While vision is an unobtrusive monitoring approach, it is prone to occlusion and lighting/camera placement issues (Agostinelli et al., 2024), but inertial capture requires the wearing of pieces of equipment and is not limited by line-of-sight (Fletcher, Johnson and Thrower, 2018). A direct comparison is not possible, as different tasks and measures of

existing studies; multimodal sensing should be investigated. Likewise, robotics solutions can alleviate repetitive and/or demanding tasks, but the benefits to workers depend on safety, task allocation and workspace configuration (Gualtieri, Rauch and Vidoni, 2021; Simões et al., 2022).

However, there are significant variations in papers on Industry 5.0 as to whether they argue for human-centricity in the context of wellbeing or in terms of production performance, and few test either argument empirically, as Briken et al., (2023) did. Definitions and architectures are still unclear in the case of an HDT (Miller and Spatz, 2022; Gaffinet, Naudet and Panetto, 2025). The seven HDT studies are conceptual, making results difficult to compare. While extensions of task-specific digital human models towards worker representations developed over time (He et al., 2024) show promise, these models need to be validated and defined, with safeguards provided for ongoing monitoring. Another, perhaps under explored factor is what's the context. The majority of the studies reviewed are from rich industrial environments.

Manufacturers in developing economies face outdated equipment, unreliable power supply and skills shortages (Muhla et al., 2025a; 2025b), which restricts the use of integrated CAE and vision systems to low-cost, robust and deployable on modest hardware solutions. Fortunately, agent-based and machine-learning architectures have been applied in Zimbabwean operations with commodity industrial controllers and plant data (Mashava et al., 2026; Senda et al., 2026), making the data backbone for human-aware twins possible in this context.

4.4 Research Gap

Several gaps remain. In most of the studies, computer vision, DHM and CAE are studied individually and not integrated together as a single system. Further studies are required in actual factories where the lighting conditions, working positions, and equipment all differ, as well as workers (Agostinelli et al., 2024). It is also important to model explicitly the difference between workers, as people vary in body size, strength, experience and susceptibility to fatigue (Chand, Zheng and Lu, 2024; You et al., 2025).

Computer vision could also be integrated directly into CAE so that real worker data can be used when making changes to the configuration of workstations. Future research should focus on posture, but also on fatigue, stress and mental workload, and the privacy of the worker and responsible use of personal data. The evidence available from developing economies is nearly all limited, and there is a need to conduct research on the efficacy of low-cost integrated systems under infrastructural conditions found in developing economies (Muhla et al., 2025a).

The learning factory is an advantageous venue for this work, and can serve as a practical test bed to validate the integrated CAE, vision and HDT systems in a realistic production setting in engineering education in Southern Africa, whilst training the skill sets and competencies as required by industry (Ndiyamba et al., 2026). As the future, these technologies could be used in a continuous process that involves workers and their movements being tracked, problems are identified, and workstation designs are simulated and modified. This may enable manufacturers to create safer workstations, to better utilise robots, and to enhance the working environment for workers.

5 CONCLUSION

The purpose of this review was to investigate the possibilities of combining CAE and computer vision in human-centred workspace design in Industry 5.0. The literature reveals that CAE and DHM are good tools for modelling human interaction with a manufacturing environment. Thanks to computer vision, it becomes possible to capture what workers are really doing, and machine learning can help automate certain aspects of the ergonomic assessment. HRC extends this by enabling machines to do physically taxing or repetitive tasks.

Digital twins represent the first step in connecting the physical factory with its virtual twin and the new shift towards HDTs adds the human worker to this virtual world, a strong step towards Industry 5.0. In general, the field is moving in clear direction: CAE and DHM, Computer Vision and Ergonomic Assessment, HRC, Digital Twins, HDTs and Industry 5.0. The greatest promise is in combining these technologies into a unified human-centred engineering framework, one that optimises the layer over the existing generation of experimental design methodologies and whose benefits have to be shown under industrial constraints of limited resources.

The ideal future manufacturing workspace might be a single system: computer vision tracking human actions, HDTs representing the person, CAE testing other workspace layouts, ergonomic models scoring the risk, and collaborative robots adapting tasks to what people can do. Industry 5.0 is all about this, it is about combining advanced manufacturing technology with human capabilities in a synergistic way rather than as separate components that are joined together.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

There is no conflict of interest.

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