Revolutionizing Industry 5.0: Harnessing the Power of Digital Human Modelling

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Abstract. Industry 5.0 signifies a significant transformation in the manufacturing sector, propelled by the convergence of advanced technologies and the incorporation of human-centric principles. This work explores the transformative potential of Digital Human Modelling (DHM) in revolutionizing Industry 5.0 across various sectors, including manufacturing, textiles, robotics, and energy. The manufacturing sector stands to benefit significantly from the application of DHM, as it enables enhanced design and optimization of production processes while considering human factors and ergonomics. DHM facilitates the development of human-centered smart factories, enabling efficient operations and improved safety management. In the textile sector, DHM offers opportunities to enhance the design of ergonomic workstations, optimize worker comfort, and improve overall productivity. In the area of robotics, DHM plays a critical role in ensuring the safety and well-being of workers. It enables the evaluation and optimization of human-robot interactions. DHM enables the design of collaborative work environments, where robots and humans can work together. In the energy sector, DHM contributes to the optimization of energy consumption, reducing carbon footprints, and promoting sustainable practices. By harnessing the power of DHM in these sectors, Industry 5.0 can achieve remarkable advancements in terms of efficiency, safety, productivity, and sustainability. This paper highlights the potential of DHM to reshape the manufacturing sector and its applications across textiles, robotics, and energy. The insights and findings presented here serve as a guide for researchers and practitioners aiming to unlock the full potential of DHM in driving the success of Industry 5.0.

Keywords: Industry 5.0 · Digital Human Modelling (DHM) · Human-centric principles · Ergonomics · Smart factories

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1 Introduction

Research indicates that trends in the application of Digital Human Modelling (DHM) are on the rise. The key technologies; such as 3D scanning, 3D modeling, language processing and artificial intelligence, set the limitations in the application fields. However, the results of real-world applications in chatbots and virtual assistants, digital influencers, corporate trainers, sales assistants, virtual product generation, and growing data-based engineering designs are already bringing radical change in the business and social landscape. Digital life will be our footprint representing an opportunity for all sectors to boost transformation to digital humans. The digital humans mimicking a real person, body language, and facial and micro gestures will be representative of identities. With the upcoming developments in artificial intelligence combined with digital human applications, there's an urgent need for the standardization of definitions such as user privacy and ethics. The standardization will support humans to have a digital life with scalable and affordable solutions, experience human connection in a digital world, and enhance inclusion between different languages and cultures. DHM refers to the process of creating computerized representations or simulations of human beings to study their interactions with the environment, products, or systems. DHM is widely used in various industries for design, ergonomics analysis, safety assessment, and human factors evaluation.

DHM plays a crucial role in the context of Industry 5.0 (I5.0) for manufacturing, textiles, robotics and energy sectors. In I5.0, DHM enables the simulation and optimization of human-machine interactions, facilitating the design of ergonomic workstations and ensuring worker safety and efficiency for manufacturing sectors. In the textile industry, DHM is utilized for garment fitting simulations and design evaluation. It allows for virtual prototyping, customization, and ensuring proper sizing and comfort for consumers. The robotics field benefits from DHM by considering human factors in robot design and programming. It facilitates in optimizing human-robot collaboration, addressing reachability and collision avoidance to enhance productivity and safety. In the energy sector, DHM plays a role in optimizing work processes and ensuring worker safety in environments such as power plants and oil refineries. It assists in identifying potential risks and designing interventions to mitigate occupational hazards. DHM is a valuable tool in I5.0, enabling human-centric design, collaboration between humans and machines, training and skills development, personalized workstations, and predictive analysis. DHM contributes to creating a work environment that maximizes productivity, safety, and well-being by harnessing the capabilities of humans and advanced technologies.

2 Literature Review

A comprehensive insight into the applications, benefits, challenges, and future directions of DHM is given in this section. Literature serves as valuable resources for researchers and practitioners interested in this field. The literature reviews are handled into four different sections such as manufacturing, textile, robotics and energy industries.

2.1 DHM and Industry 5.0 in the Manufacturing Industry

Industry 5.0 has revolutionized the manufacturing sector by leveraging rapid technological advancements to enhance process performance. However, the introduction of new technologies also brings unforeseen challenges and potential problems for workers in terms of safety and ergonomics. By proactively addressing these challenges, manufacturers can create a work environment that not only maximizes performance but also safeguards the well-being of their workforce. Overall, the combination of DHM and I5.0 in the manufacturing industry emphasizes the integration of human capabilities, advanced technologies, and data-driven approaches.

Agnusdei et al. proposed a methodology for assessing the current applications of Digital Twin (DT) technologies, with a specific focus on the safety domain. To validate the proposed framework, an analysis of existing DT applications in scientific literature was conducted. The findings indicated that while the number of DT applications in the safety field might not be extensive, the existing tools demonstrated a high level of complexity. This complexity contributed to the reliability and effectiveness of these tools in addressing specific safety problems. The study indicated that DTs found substantial application in various sectors. Manufacturing accounted for the largest share (59%), driven by the adoption of I4.0 tools. In mobility systems, DTs were primarily used to ensure the safety of autonomous vehicles within buildings and for self-driving cars. Another noteworthy sector was civil infrastructure, which represented 11% of DT adoption. In this field, DTs supported condition monitoring and testing to optimize cost design and enhance safety performance. However, the pioneering sectors of aeronautics and space received relatively less attention despite being where DTs were initially developed. Similarly, the energy sector has only recently begun developing applications for DTs. The study also stated that the majority of current DT applications (63%) were focused on addressing safety concerns related to equipment and machinery. This implied that DTs were being used to monitor and manage risks associated with the use and presence of these assets. Additionally, a significant portion (34%) of DT applications involved addressing safety issues arising from interactions between humans and machines. However, it was mentioned that there was limited research focusing specifically on risks solely attributed to human behavior, with only one paper identified in this area [1].

Caputo et al. highlighted the significance of integrating assembly line design and ergonomics to create human-centered smart factories. It emphasized the use of numerical procedures for ergonomic assessments, which could significantly accelerate the iterative design process compared to traditional experimental methods. By considering ergonomics as a design variable rather than just a constraint, a preventive evaluation of ergonomic indexes became feasible, facilitating the validation of the work process design. In the research paper, a DT of a Fiat Chrysler Automobiles (FCA) assembly line station was introduced to validate the proposed numerical procedure and design approach. DT served as a virtual replica of the real station, allowing for simulations and analysis. Furthermore, the study compared the numerical results obtained from DT, specifically in terms of evaluating an ergonomic index, with the experimental results derived from analyzing data collected during a physical experimental session. By utilizing DT and conducting this comparative analysis, the researchers demonstrated the effectiveness of the proposed methodology and its ability to provide reliable results in line with the traditional experimental approach [2].

Zhan et al. conducted in an air cargo cold storage warehouse to show the viability and effectiveness of the proposed system and methods in a practical case. The researchers provided detailed explanations of the implementation process, aiming to facilitate easy replication and application of the study in similar contexts. Furthermore, the study focused on analyzing the influence of learning features, specifically distance and vibration, on the performance of anomaly detection. Through experiments and analysis, valuable insights were gained, shedding light on the importance of these factors and their impact on the overall system. The findings and lessons derived from this study had the potential to serve as a valuable reference and inspiration for researchers and practitioners facing similar challenges in their respective fields. The study offered practical insights and ideas that could contribute to meeting similar needs effectively in real-world applications. In the study, the Safety-Oriented Occupational Safety Management System (SOSMS) for monitoring occupational safety and sensing their locations in real-time was developed. The enhanced information traceability and visibility via intelligent services activated more efficient operations and safety management [3].

Reiman et al. performed a systematic search, among 336 research articles. 37 papers were selected for analysis, employing a human-centric work system framework derived from the Human Factors and Ergonomics (HF/E) literature. The analysis specifically examined the challenges linked to technological development within micro- and macro-ergonomics work system frameworks. Drawing upon the insights gained from the literature review, the researchers proposed a maturity model at the organizational level. This model aimed to optimize the overall sociotechnical work system performance in the context of rapid technological advancements within the manufacturing industries. By considering the characteristics outlined in this model, organizations could navigate the challenges associated with technological development and foster improved work system outcomes [4].

Guo et al. aimed to explore innovative architectures and approaches for Manufacturing Planning and Control (MPC) in the context of I4.0 manufacturing in the study. It highlighted the need for quantitative investigations into the effects of synchronization oriented MPC on enhanced economic, social, and environmental benefits in order to evaluate the performance of the proposed approach. Additionally, the synchronization-oriented MPC exhibited potential benefits that aligned with the goals of I5.0, which emphasized a sustainable, human-centric, and resilient industry. These benefits included enhanced customer-centric value creation, increased resilience, improved human-centric operational interaction, and reductions in energy consumption and carbon footprint [5].

In a recent development, the European Commission officially announced I5.0, highlighting the significance of integrating rapidly evolving technologies into the production process while prioritizing the needs of workers and adopting a customer-centric perspective. This initiative underscored the importance of leveraging advanced technologies to enhance productivity and efficiency while ensuring the well-being and satisfaction of both workers and customers [6].

Table 1 indicates that the intersection of DHM and I5.0 are described within different aspects. This intersection emphasizes the importance of human-centric design, collaboration, training, personalization, and real-time optimization. DHM enables the integration of humans and advanced technologies, fostering productivity, safety, and well-being in the evolving industrial landscape.

Table 1. The Intersection of Digital Human Modelling (DHM) and Industry 5.0

Aspect	Description
Human-Centric Design	DHM enables the analysis and optimization of workstations, processes, and products to enhance human safety, well-being, and productivity
Ergonomics and Safety	DHM supports the emphasis of I5.0 on ergonomics and safety. It enables the assessment of human factors, such as reachability, comfort, and user interactions, to design work environments and processes that prevent injuries, musculoskeletal disorders, and promote worker well-being
Collaborative Robotics	DHM assists in the development and integration of collaborative robotic systems in I5.0. It allows for the simulation and analysis of human-robot interactions, ensuring the safety, efficiency, and intuitive collaboration between humans and robots in shared workspaces
Human-Machine Interfaces	DHM contributes to the design and optimization of human-machine interfaces (HMIs) in I5.0. It helps create intuitive and user-friendly interfaces that enable interactions between humans and intelligent systems, promoting efficient and effective operation and control
Workforce Training	DHM supports the focus of I5.0 on workforce training and upskilling by enabling the creation of virtual training environments. Workers can practice tasks, improve skills, and learn how to collaborate with intelligent machines in a safe and controlled manner
Customized Manufacturing	DHM aids in achieving customized manufacturing in I5.0. By simulating and analyzing human capabilities, DHM helps optimize production processes to accommodate human skills and adaptability, allowing for flexible and personalized manufacturing approaches
Product Development	DHM plays a role in product development within I5.0. By simulating human interactions, DHM helps optimize product design, considering factors like usability, comfort, and safety, resulting in products that meet human needs and preferences more effectively
Data-Driven Decision Making	DHM provides valuable data for data-driven decision making in I5.0. By capturing and analyzing human-related metrics, such as ergonomic assessments, performance data, and user feedback, DHM helps inform decision-making processes to improve processes, products, and worker experiences

2.2 DHM and Industry 5.0 in the Textile Industry

DT investigates the body of knowledge and state-of-the-art technology in the field of DHM and its applications in the apparel and fashion industry. DHM is the science of representing human beings based on the physical properties, properties, and even behaviors of the body's surface in visualized, virtual models of real people. These models can be used on their own or integrated with other computer-aided object design systems to create or explore designs of dress or car products by using model mannequins and their visual twin to real people. They serve as fast and inexpensive computational tools for evaluating human functional systems and human-system interactions [7].

The use of the human body as a digital model has become an indispensable application for the clothing industry by applying realistic images of human. Current rendering methods have achieved great things for the model industry in creating realistic images of humans who have captured the whole body in detail effectively [8].

Product avatar as a digital counterpart to a physical individual product. The relevance of product-equivalent digital counterpart results from the expected benefits of a product. Product avatar as a digital counterpart to a physical individual product. The relevance of product-equivalent digital counterpart results from the expected benefits of a product. DT is a well-matched digital image that will exist along the product life cycle, from product conception and design to use and maintenance, so, it will be in the past, present and possible future of the product states and helpful for the development of the product related [9].

By implementing 3D body scanning systems in the apparel industry, garment manufacturers can enhance the efficiency of their production processes, improve sizing accuracy, and provide customers with a better fit. Virtual try-on experiences can also be created, allowing customers to visualize how garments will look on their own bodies before making a purchase. There are too many companies such as Cyberware, Hamano, Vitronic, TecMath, TC2, Telmat, Wicks and Wilson, and Hamamatsu which are currently appropriate for use in the apparel industry for the measurement of human body size. The principle of the 3D body scanning systems is based on optical triangulation by non-contact methods using either laser or light projection systems. The body scanner scans the surface of a 3D object, projecting either laser or light and using vision devices to capture the shape of the object. The data from the scan is extracted by a software program. Cyberware, Vitronic, Hamano, TecMath, and Vitronic use a laser, and TC2, Wicks and Wilson, Telmat, and Hamamatsu use a light source and various techniques for capture. TC2 and Wicks and Wilson use similar methods by using white light sources, however, Hamamatsu uses a near-infrared light LED with the PSD method. The scanner uses an eye-safe laser on the person being measured and a noncontact method. Two or more cameras capture the distortions created by the body and can measure the hidden side of the body. The scanner produces a so-called point cloud which will be captured about 100,000–300,000 data points in a few 12 s which is then the body's 'landmarks' – shoulders, chest, navel, hips, and so on – are identified using image processing software, so every customer will have a DT. Finally, a virtual tape measure is applied relative to the body landmarks to extract nearly 130 key sizes and shape measurements [10, 11] (Fig. 1).

Fig. 1. Digital Human Models for Dress Fitting [11]

The human model known by the acronym RAMSIS (Computer-Aided Anthropological-Mathematical System for Occupant Simulation) was a collaborative development involving the Chair for Ergonomics at the Technical University of Munich, the Catholic University of Eichstätt, the Research Association for Automotive Technology (FAT), and the company Tecmath, which subsequently evolved into the manufacturer Human Solutions. The main functions of the program enable ergonomic examinations of cockpits in the automotive, aircraft, and construction machinery industries, for which the RAMSIS Automotive, Aircraft, and Industrial Vehicles packages are available from the manufacturer Human Solutions. Databases with several populations of different ages, differentiation according to percentiles, somatotypes, and inclusion of acceleration. This includes the companies that are currently developing and selling the systems (manufacturers), the platform, the systemic structure, the essential anthropometric model properties, and functions for manipulation and analysis. In this context, a skeleton is to be understood as a connection of stretches and joints that represent the segments and the (rotatory) degrees of freedom between the segments. These skeletons represent the basis of anthropometry, posture adjustment, and movement of human models. In some systems, a skeleton in the original sense of the word, referred to here as a volume skeleton, can still be used. This information can be useful for assessing contact surfaces with nearby objects, determining the thickness of tissue between the skin and bones, or measuring the distance to an external object or structure [11, 12] (Fig. 2).

Once it has the 3D control mesh of buckling patches for the whole garment, then it will procedurally generate the clarified buckling mesh, in order to find the final geometric shape geometry. The reason for moving a suit's control points is to eliminate any local inputs inside the digital manikin on the digital manikin (Handling collisions). It is needed a physical simulation should be processed on control points to handle the action of external forces (Mimicking and estimating the action of external forces). Skirts can be mimicked by creating compression perpendicular to the major axis. To get a real simulation, the twist can be used to model a sideways wind effect [11, 13]. (Fig. 3).

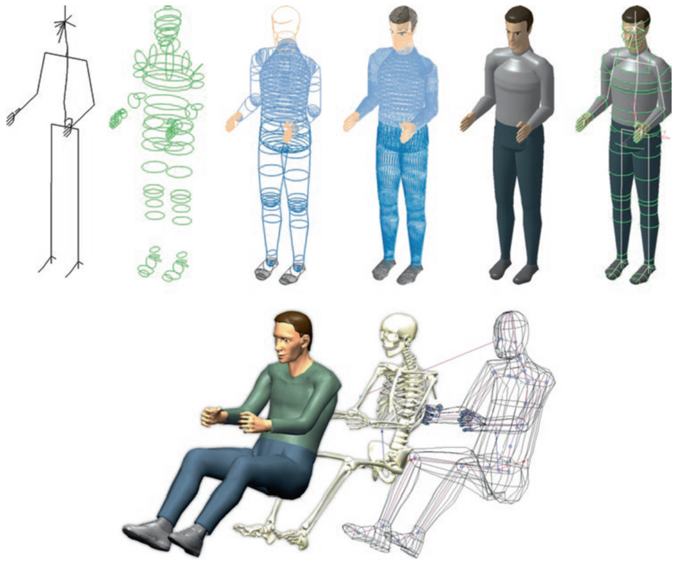

Fig. 2. Creating Ergonomic Digital Human Models with Skeleton, Volume Skeleton, and Envelope Surfaces for Skin and Clothing: Examples Using Human Builder (Above) and RAMSIS (Below) [11]

Fig. 3. Virtual Clothing and Real Replicas Sewn from the Patterns [11]

2.3 DHM and Industry 5.0 in the Robotics Industry

DHM and Industry 5.0 have significant implications for the robotics industry from literature as below. Table 2 indicates the application area of DHM in the robotics industry according to I5.0.

The intersection of DHM and I5.0 in the robotics industry involves leveraging DHM techniques and tools to enable safe and efficient human-robot collaboration, optimize

Table 2. Applications of DHM in the Robotics Industry According to Industry 5.0.

Application Area	Description
Human-Centric Design	DHM enables human-centric design approaches by integrating human factors and ergonomic considerations into the development of robotic systems
Collaborative Robot Deployment	DHM aids in the deployment of collaborative robots by simulating human-robot interactions, ensuring safety, ergonomics, and task optimization
Adaptive Work Environments	DHM supports the creation of adaptive work environments that can dynamically respond to changes in production requirements and human operator needs
Augmented Training and Support	DHM facilitates augmented training and support systems, allowing workers to learn and interact with robots in virtual environments before real-world implementation
Predictive Maintenance	DHM assists in predictive maintenance of robotic systems by analyzing human-related factors and ergonomics to detect potential maintenance issues in advance
Continuous Improvement	DHM contributes to continuous improvement efforts by analyzing human-robot collaboration data, identifying inefficiencies, and suggesting process optimizations

robotic systems, facilitate training and programming, and ensure ergonomic considerations. DHM analyses human-related factors and ergonomics to detect potential maintenance issues in advance. This proactive approach to maintenance, aligned with I5.0 principles, helps minimize downtime, optimize resource utilization, and ensure the continued performance of robotic systems. DHM contributes to continuous improvement efforts by analyzing data on human-robot collaboration. This data-driven approach enables organizations to identify inefficiencies, optimize processes, and enhance overall system performance.

Mazumder et al. aimed to examine the incorporation of DT into robotics within the context of I4.0 in the research paper. It recognized that with the advent of I4.0, various cutting-edge technologies such as cyber-physical systems, IoT, robots, big data, and cloud computing emerged. However, understanding how these technologies could be interconnected or fused to enhance collaboration and functionality was crucial to fully realize the potential of I4.0. The paper searched for addressing the relative originality of DTs in robotics and their unparalleled possibilities. It emphasized the need for a comprehensive evaluation of existing literature and the development of a framework to advance research in DT-integrated robotics. By exploring trends in both high and low research saturated robotic fields, the paper aimed to identify gaps, emerging trends, dying trends, potential scopes, challenges, and viable solutions in the integration of DTs with robotics. The main objective of the study was to suggest a framework based on a hypothesis for the future direction of robotics integrated with digital technology. This framework would serve as a guide for further research and development in the field, providing insights into the potential benefits, challenges, and opportunities associated with the integration of DTs and robotics within the I4.0 context [14].

Ma et al. conducted to demonstrate the feasibility and effectiveness of the proposed method in a practical human-robot collaboration scenario in a case study of the research paper. The case study showed how the four-tuple DT model, and the model consistency method can enhance the performance and coordination of human-robot collaborative tasks. It contributed to the advancement of human-robot collaboration by introducing a DT model tailored to the specific requirements of collaborative scenarios. The proposed model consistency method ensured the accuracy and reliability of the DT representation, further enhancing the potential for successful human-robot collaboration [15].

Liu et al. proposed an approach that utilized DT technology to facilitate the effective transfer of Deep reinforcement learning (DRL) algorithms to physical robots in the context of assembly-oriented industrial grasping. A DT was a dynamic and up-to-date representation of a physical robotic grasping system. In this approach, two parallel training systems were established: a physical robotic system and a corresponding DT system. Both systems would take inputs in the form of virtual and real images. The output of the DT system was used to correct the real grasping point, enabling accurate grasping in the physical robot. Overall, this research offered a valuable contribution to the field of reinforcement learning in robotics. By utilizing DTs, the proposed method enhanced the adaptability and flexibility of robots, enabling them to handle complex challenges in real industrial scenes, including illumination variations, occlusions, and complex task scenarios [16].

2.4 DHM and Industry 5.0 in the Energy Sector

Too many companies have already embarked on the digital transformation age to become competitive markets by using these technologies. And these days, with many global initiatives to be aware of a zero-carbon energy sector, using DT technology has emerged as the energy management solution to provide resiliency in the benefits industry. As the utility industry begins to alter to greener renewable energy sources, the multiplicity of energy sectors is now needed for the use of DTs for efficient energy production and management. Digital Twin Energy Management is the process of planning, organizing, and controlling DT technology that is becoming a digital transformation at companies like General Electric.

DTs are real-time digital counterparts that virtually represent physical objects in their physical environment, such as wind turbines and solar systems. DTs offer real-time information about the use and performance of utility infrastructure. With sensor data standing uploaded to the cloud, companies can use machine learning algorithms to simulate what-if scenarios to monitor errors and deviations. This type of monitoring is the cornerstone of I4.0 manufacturing - anticipating errors and risks. Furthermore, using predictive maintenance if systems will need checking and maintenance. DT technology increases energy efficiency and reduces environmental impact. The management of DTs in the utility industry should be integration and collaboration between machines to humans and enhanced communication along with equipment, suppliers, applications, systems, and people [17].

According to the Economist Intelligence Unit's Energy Outlook 2023, global energy consumption will continue to grow by 1.3% in 2023 during a period of economic recession and high energy prices. Therefore, the energy industry must keep up with the changes. The use of artificial intelligence in the energy sector offers several major advantages. Essentially, AI technologies provide much more productive work processes in energy sectors.

1. AI-managed smart grid networks ensure fast energy and data flow between the energy supplier and consumers. This type of network makes possible data management processes such as acquisition, storage, and analysis. Subsequently, through advanced analytics and machine learning, it can be used the best predictions method which is available data to prevent faults in power generation assets and accurately forecast energy demand.
2. AI-driven programs make it possible to get accurate forecasts and forecasts leading to better use of renewable energy [18].

DTs use data from sensors installed on physical objects to define their real-time performance, operating conditions, and changes in objects over time. For example, unachievable subsea trees used in the open sea oil or gas areas can be fitted with various sensors to generate data on different performance conditions of the subsea trees. This data includes the temperature of the object, product performance, and environmental conditions. The data is then processed through a system of computers and servers and applied to its virtual copy. With an updated virtual model, operators can run simulations, analyze product performance, and discover potential areas for improvement. They can then apply this knowledge to the underwater tree or original physical object to optimize its performance. There are three types of twins,

- Digital product twins. Virtual models created by DTs can validate a product's performance while monitoring its real-time capabilities in the physical world.
- Digital production twins. A production DT can predict how well a process will perform before it even began in production.
- Powerful DTs. Energy companies obtain broad amounts of data about their operational effectiveness and product distribution [19].

DHM and I5.0 hold significant potential for the energy sector. DHM can enhance worker safety and optimize ergonomic design, while I5.0 enables the integration of human workers with advanced technologies for improved productivity and value creation. These concepts, alongside DT technology, can drive digital transformation and bring numerous benefits to the energy industry. By embracing I5.0 principles, the energy sector can achieve improved operational efficiency, cost savings, and better utilization of human capital. It enables companies to employ technological advancements while empowering human workers to contribute their expertise, judgment, and creativity in complex energy management tasks.

3 Conclusions

In conclusion, the integration of DHM into the framework of I5.0 presents immense potential for revolutionizing the robotics industry. By harnessing the power of DHM, organizations can unlock new opportunities for human-robot collaboration, enhance safety and ergonomics, and drive overall productivity and efficiency in manufacturing processes. DHM enables human-centric design, ensuring that robotic systems are optimized for interaction with human operators. It allows for the simulation and evaluation of human-robot interaction scenarios, leading to the development of intuitive interfaces and safe work environments. Through augmented training and support systems, DHM empowers workers to acquire the skills and confidence needed to collaborate effectively with robots. DT technology involves creating a virtual replica or simulation of physical assets, processes, or systems. It allows organizations to monitor, analyze, and optimize their operations in real time. DT energy management is a vital component of the digital transformation taking place in the utility industry. It offers companies the ability to optimize energy production and management, align with renewable energy initiatives, and achieve greater operational efficiency and sustainability.

Looking to the future, there are several suggestions for further harnessing the power of DHM in I5.0. Continued research and development in DHM technologies will enhance their capabilities in accurately modeling and simulating human behavior, ergonomics, and interaction. This will enable more precise optimization of robotic systems for improved performance and user experience. The integration of AI and machine learning algorithms with DHM can lead to more sophisticated models and simulations. This can enable robots to adapt to changing human behaviors, preferences, and work requirements, fostering even more collaboration. The collaboration between humans and robots will reach new frontiers, revolutionizing manufacturing processes and shaping the future of I5.0.

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